AN ENSEMBLE APPROACH FOR FOOD WASTE MANAGEMENT SYSTEM USING COMPUTATIONAL INTELLIGENCE TECHNIQUES

A Thesis

Submitted in partial fulfillment of the requirements for the

Award of the degree of

DOCTOR OF PHILOSOPHY

in

(Computer Science and Engineering)

By

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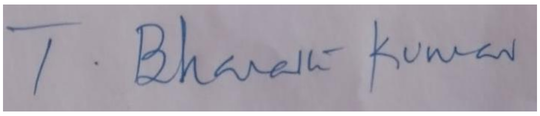
2024

DECLARATION

I, hereby declare that the presented work in the thesis entitled **"An Ensemble Approach for Food Waste Management System using Computational Intelligence Techniques"** in fulfillment of the degree of **Doctor of Philosophy (Ph. D.)** is the outcome of research work carried out by me under the supervision **Dr. Deepak Prashar**, working as **Professor**, in the **Computer Science and Engineering** of Lovely Professional University, Punjab, India. In keeping with the general practice of reporting scientific observations, due acknowledgments have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.



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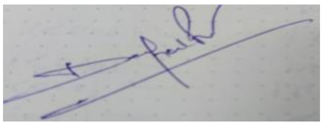
CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled **"An Ensemble Approach for Food Waste Management System using Computational Intelligence Techniques"** submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the **Computer Science and Engineering**, is a research work carried out by **Thatiparthy Bharath Kumar**, **41900466**, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.



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LIST OF PUBLICATIONS

1. Published a paper cited as Kumar TB, Prashar D. **Review on Efficient Food Waste Management System Using Internet of Things. International Journal of Current Research and Review** [Internet]. Radiance Research Academy; 2021;13(06):142–9. Available from: http://dx.doi.org/10.31782/ijcrr.2021.13603.

2. Published a paper cited as https://www.mililink.com/upload/article/232635633aams_vol_215_march_2022_a31_p2751-2763_t._bharath_kumar_and_deepak_prashar.pdf " Assessing household food waste in Hyderabad city".

3. Presented and published a paper on "Exploration of research on the Internet of Things Enabled Smart Agriculture" Conducted by the International Conference on Research in Science, Engineering, Technology, and Management (ICRSETM-2020).

4. T. Bharath Kumar, Deepak Prashar, Gayatri Vaidya, Vipin Kumar, S. Deva Kumar, F. Sammy, "A Novel Model to Detect and Classify Fresh and Damaged Fruits to Reduce Food Waste Using a Deep Learning Technique", Journal of Food Quality, vol. 2022, Article ID 4661108, 8 pages, 2022. https://doi.org/10.1155/2022/4661108.

5. Presented and published a paper on "Analysis of Different Techniques Used to Reduce The Food Waste Inside The Refrigerator" Conducted by IEEE Explore/ ICDCECE-2022.

Abstract

The world's food supply is decreasing at an alarming rate since there needs to be more effective solutions for dealing with food waste at many levels, including households, restaurants, and food supply chains. Most food waste in homes and restaurants is due to overcooking and other causes. Food waste reduction in the quantity and quality of meals results from choices and actions made by consumers, restaurants, and retailers. The ability of the home to obtain enough food to satisfy the nutrient needs of every family member is called household food security. Sufficient food supplies to meet the population's demands for a healthy and active life are critical in the household and national food security relationship. This implies that food is secure in terms of quality, quantity, safety, cultural acceptance, and aspirations for the future; a foundation for this is provided by national food security. In the end, ensuring that every household and every member of the family has access to enough food is more crucial. Most wasted food comes from homes, and one of our goals was to cut down on this by classifying food as either fresh or damaged. At this point, it is also essential to identify fruits that have begun to decay. Although it is common practice for individuals to categorize fruits as either healthy or rotting, fruit farmers find that this practice could be more helpful. In contrast to humans, robots do not become exhausted from performing the same action repeatedly.

As a result, the agricultural business has made the detection of flaws in fruits one of its proclaimed goals to reduce the amount of labor, waste, manufacturing expenses, and time spent on the process. If the flaws are not identified, a diseased apple can spread to a healthy apple. As a direct result, there is a more significant potential for wasted food, leading to several other issues. The input photos determine which fruits are healthy and which have been spoiled. This study used fruits, including apples, bananas, and oranges. While CNN is responsible for obtaining fruit picture properties, the Softmax technique is used to identify images of fruits as either fresh or rotting. The comparative result is validated using existing systems such as VGG16, AlexNet, Dense Net, lightweight CNN, CNN, Ensemble CNN, Proposed CNN, and Proposed ensemble CNN model. On the benchmark “fresh and rotten” benchmark dataset, the suggested ensemble approach is assessed using conventional performance criteria.

The performance indicators are computed using the test image's actual and anticipated class labels from the Fruits fresh and rotting dataset. The precision score reflects the probability of accuracy, and the recall score signifies the probability of completion. The harmonic average of recall and precision is the F1 score. The model performs accurately, precisely, and entirely according to average performance measures. The accuracy, precision, recall, and F-score results evaluate the new and rotten fruit classification and food waste management. To execute with more samples, CPU machines are not comfortable. So, in such cases, high-end configurations are required, meaning GPU machines may be needed for implementation. The outcomes of our study demonstrate that, when categorizing fresh or damaged fruit, our suggested Single and ensemble method outperforms the existing approaches by 95.14% and 99.39%.

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First of all, I pay my gratitude to the Almighty for conceding me the opportunity and strength to accomplish this assignment. I would like to thank my esteemed supervisor, Dr. Deepak Prashar for his valuable supervision, support, and tutelage during the course Ph.D. of my Ph.D. degree. I owe my deep sense of gratitude to the dynamic academician and generous guide, who all along has been an immense source of encouragement to me in completing this work. He spared time for academic interactions with me. My heartfelt gratitude and indebtedness go to my loving parents (Shri. T V Ratnam and T Punyavathi) for their blessings and encouragement. Finally, I very sincerely acknowledge the cooperation of my friends and colleagues, who helped me a lot during this work. I would like to thank all the authors whose studies have been quoted in this study.

T. Bharath Kumar

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF FIGURES

Chapter – 1

Introduction

The word or terminology food waste reduction is the primary background of our research work and is also discussed in the current chapter with a few examples, significant causes of food waste, challenges, and also the measures needed to take shortly to promote the reduction of food waste as it is the primary concern for our globe to save and return to the younger generations not to suffer from the availability of the food. The introductory chapter gives insights into food wastage worldwide, with some statistics from reputed organizations. Similarly, the chapter also gives an idea about the environmental issues that come from unexpected waste from different sources due to various reasons, as discussed.

1 INTRODUCTION

Food waste reduction in the quantity and quality of meals results from choices and actions made by consumers, restaurants, and retailers. The ability of the home to obtain enough food to satisfy the nutrient needs of every family member is called household food security. Sufficient food supplies to meet the population's demands for a healthy and active life are critical in the household and national food security relationship. This implies that food is secure in terms of quality, quantity, safety, cultural acceptance, and aspirations for the future; a foundation for this is provided by national food security. In the end, ensuring that every household and every member of the family has access to enough food is more crucial. The world's population increased from 1.6 billion to 7 billion [1]. This population expansion has brought on the central issue of hunger. Growing concern has been expressed about the techniques and outcomes of contemporary industrial agriculture due to problems like food scarcity and inadequate supply. In particular, synthetic fertilizers and chemicals have practically changed the agriculture sector with the timely ripening of fruits and vegetables, insect control, and enhanced land productivity, which has dramatically helped to satisfy the food requirements of an expanding population. Because of the industrialization of the food chain, vast amounts of food are now produced with a minimum of labor. Although automation has provided numerous advantages to humans, it has also had several unfavorable effects, including the destruction of the environment, unequal food distribution, economic loss, and many others. The current food-saving systems have many challenges to controlling wastage in production and other factors of food waste. The most significant developments over the past century have been brought about by the growth in agriculture with the discovery of the plow, the introduction of agricultural chemicals, and ongoing industrialization. Nearly 50% of the Indian population relies on these stages of food production for survival, according to research on them. The agri-food chain is a significant source of income for the populace, either directly or indirectly. Unfortunately, the data reveals that 20 crore Indians go to bed hungry every night, and the country is ranked 67th out of 122 in the 2011 Global Hunger Index. However, the country's population must be fed more food to feed everyone. According to reports from the Food and Agriculture Organization [FAO] [1], this issue worsens daily. Around the world, 130 million tonnes of consumable substances are lost yearly. The quantity of carbon dioxide (CO2) released into the environment from food waste is equivalent to emissions of greenhouse gases, with 3.3 billion tonnes emitted into the environment each year. The total quantity of water required to produce food that is thrown away or lost is comparable to the volume of water that flows through the Volga River in Russia or to the amount of water that occupies three times as much of Lake Geneva in a single year [3]. Reducing uneaten prepared food in the commerce and purchasing sectors is the objective of Challenge 12.3 of the Global Goals, which aims to eradicate food losses, particularly losses after harvesting, along with contributing chains. The initial study of the Food Waste Index conducted by the United Nations Environment Programme (UNEP) provides information on the magnitude of food waste and its underlying structure. With this information, countries can establish baselines and check the status of the Sustainable Development Goals, which is a significant goal (SDG). According to the survey findings, homes, companies, and the food service industry throw away 931 million tonnes of food annually. This waste is generated domestically in roughly 570 million tonnes [5]. The data also reveals that low, middle, and high-income countries lose an average of food per person-year is about 74kg, which suggests that most nations have room for improvement. Furthermore, there is a rise in food waste across various sectors, including packaging, retail, post-harvesting, storage, and domestic.

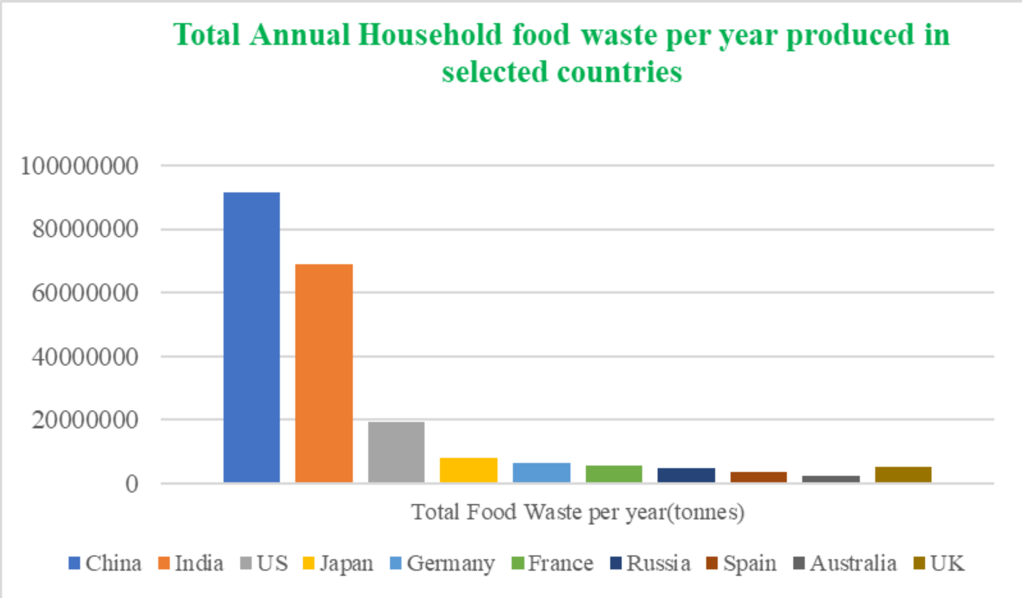

Figure 1.1 Global Food Waste Estimates per year

The globe has also recognized the need to reduce food waste and included it as one of the SDGs (12.3). The global food waste estimates are depicted in [Figure 1.1] to understand the world's perspective on food waste statistics from selected countries.

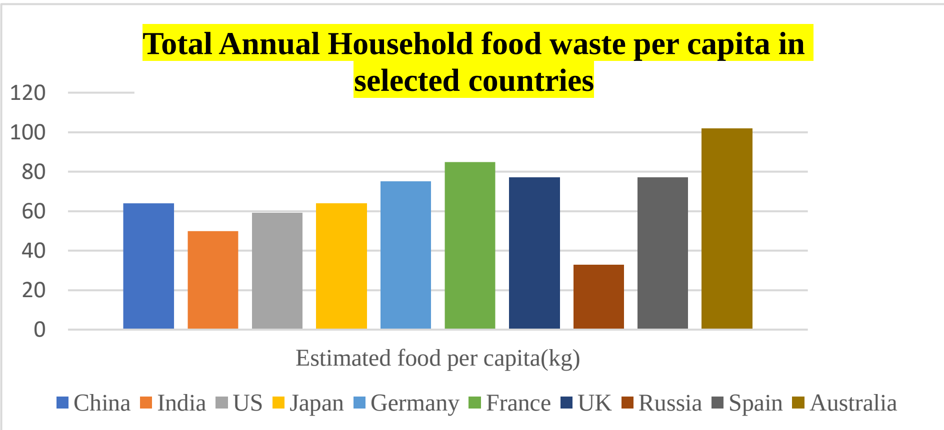

Figure 1.2 Global Food Waste Estimates per capita

Similarly, food waste per capita is also mentioned in figure [1.2] to the world's current food waste situation. The literature and reports also support that most food wasted in the nation comes from homes. Damage, overcooking, plate waste, rotten food, and other factors are the causes of all domestic food waste. For some time to preserve, items will be stored in the refrigerator, and then they will be utilized as needed. However, because intelligent refrigerators are expensive, most people use traditional refrigerators, making it challenging to understand whether the items stored within are damaged, fresh, or have passed their expiration date, for example [7, 8]. Regular refrigerators use emerging technologies like deep learning and the Internet of Things to identify the food stored inside. We can employ specific sensors to determine when a packaged item kept in a refrigerator has expired, and the user will then accept a message advising them of this. Research is being done to reuse traditional refrigerators by adding gadgets like cameras to compartments. Additionally, models are being built to determine how to most reliably recognize the food within the fridge using deep learning techniques [9]. Convolutional Neural networks (CNN) do picture detection and food item classification quite effectively with new and damaged stages. This study identified three fruit varieties, apples, oranges, and bananas [10]. Since fruits have a wide range of shapes, colors, sizes, textures, and other features, classifying them can be challenging. There are many applications for a reliable and durable solution to this problem. One practical and urgent use of such a system is determining supermarket prices. Cashiers at supermarket checkout counters conduct a critical task called fruit classification. These cashiers must be able to recognize both the kind and variety of fruit to determine prices. Reduced consumer and retail food waste and minimal supply chain losses are required to meet SDG 12.3's targets. Food Waste Index Report aims to support SDG 12.3 in two different ways. This report provides a changed estimate of the world's food waste based on the extensive data set, analysis, and modeling of food waste. Even though intervals for estimates vary by place and industry, national perception about the wastage of food offers new perceptions of the extent of the issue and the significant potential in different income countries. Secondly, by examining food waste in the retail and household sectors, this research recommends that Sarkar track the country's progress toward reducing food waste [7]. Governments can utilize this method to generate reliable statistics to support national garbage avoidance initiatives. People of all ages and professions feel the effects of food waste. Tierce of the food available for human utilization is wasted each year. Deep learning techniques have in the past outperformed many well-known methods in comparable fields, like image categorization [11]. Reduced intermediate representations handle data samples, eliminating the requirement for additional preprocessing during feature extraction. Several commercial groups use other devices to collect data and analyze individual offers to the global problem of detecting and reducing food waste. These devices monitor the amount and type of food that is wasted. Some businesses are implementing unbiased observer devices to collect data and determine how each employee contributes to the overall problem of commercial food waste to identify and reduce it. These gadgets record the quantity and kind of food thrown away [12]. Similarly, machine learning is used in many ways daily to reduce food waste. Price fluctuations in the chain will depend on the locations of interventions. They will have different effects upstream in the distribution chain to the cost change location. Participants in the supply chain would interpret it as a change in the cost of their inputs, as opposed to those in the later stages. However, altogether, the decrease in retail waste may result in consumers being able to purchase food at a lower price, which improves their well-being.

1.1 The rise in the Basic Human Right to Food

It is essential to realize that the evolution of food results from the appearance of humans on Earth. Since the beginning, food has been a necessity for human existence. In his speech, Swami Vivekananda urged the youth to increase crop production to satisfy public demand. He emphasized the importance of using new technologies to boost manufacturing and gave the necessity to create food a higher status than even doctrine. Humankind tends to have known the value of food from the beginning of the evolution of life on Earth. Therefore, it was also viewed as wicked to waste food grain. The idea of food waste was fundamental to us as Indians and our ancestors, as is clear from the scriptures and antiquated laws that are still in existence now. In prehistoric society, food was equated to life. Not only were Indians concerned about food waste, but they also regarded food as having a special status in life. Ancient religious texts expressly address the fair and equitable distribution of food and certain safeguards for its security. Since the development of human society, people have gone through various stages of life, from hunters to gatherers of food to a community that lives in a specific location while being distinct from other animals. Sharing food and other goods among society members became a habit for humans once society was formed, making it a particular pattern. As a result, food was distributed relatively in ancient Indian culture. Introduces the idea of a kingdom as a result of human society. When kings ruled, it was the responsibility of the ruler or king to feed everyone who lived in his domain. The distinction between a moral obligation to supply food and a right to food is that the former gives rise to a claim that can be enforced, while the latter cannot. As eras changed, laws and regulations replaced scriptures as the primary means of governing society. It becomes necessary to enact legislation on a national and international level to safeguard peoples' fundamental rights, specifically their right to food. However, the group did not receive enough food to lead a healthy life due to a lack of effective law or improper execution. Thus, it caused malnutrition and hunger in a particular group of people. As a result, it placed unnecessary pressure on the government of any nation to supply basic, nourishing food to its citizens, especially to expectant mothers who would otherwise give birth to newborns who would be malnourished from a lack of enough nourishment. It has been 73 years since India gained its independence. Yet, despite this, insufficient concrete steps are being taken to ensure every Indian has access to food, one of their most fundamental human rights. As is well known, the Green Revolution led to a significant rise in food output. And it changed India from a state that imported food to one that exported food. Despite increased output, the government could not sustain family food and nutritional security because it lost momentum. People continue to go hungry because government programs in this area are not being implemented, which increases poverty and reduces the purchasing power of impoverished households. Therefore, the increased output does not necessarily result in increased household food security or decreased hunger. In India, the idea of the right to food has evolved from being about feeding the entire country to now being about providing for the vulnerable [2].

1.2 General Reasons for Food Waste

There are many different reasons why food is lost or wasted. On-farm losses have several significant root causes, including insufficient harvesting time, unfavorable weather, harvesting and handling procedures, and difficulties with crop selling. Significant losses are brought about as a result of inadequate storage conditions as well as decisions made earlier in the supply chain that predispose things to have a shorter shelf life. For example, adequate cold storage may be essential to preventing both quantitative and qualitative food losses. Infrastructure and effective business logistics are crucial to reduce food waste loss during shipping. Processing and packing can help preserve food. However, inadequate facilities, technological failures, or human error can result in losses.

Food waste at the distributor stage results from several factors, including food products' short shelf lives, the need to meet aesthetic standards for color, form, and dimensions, and shifting consumer requests. Buyer decay is frequently due to inadequate meal and procure planning, overbuying, label ambiguity, and improper indoor storage. Fruits and vegetables must be treated carefully after being harvested to preserve their quality because they are highly perishable. Transportation represents a significant loss point in the food chains of vegetables and fruits, mainly because of improper bulk packing and inadequate relative humidity and temperature control. Quality loss due to mechanical damage is manifested by bruising and produces shape deformation, cracking, and punctures. An extensive range of elements, including biological, precursor, biochemical, microbiological, chemical, logistical, mechanical, physiological, physical, technical, organizational, and behavioral psychological causes, including those brought on by marketing, etc., can contribute to food waste. An integrated viewpoint across the food chain is necessary to determine the reasons behind food waste. The following is a list of why food waste frequently happens at different links in the food chain [Figure 1.2].

Figure 1.3 Causes of Food Waste

1.2.1 Production

Food production composes the modern methods of producing food in agricultural fields and animal husbandry. These modern methods are mostly the product of scientific developments in farm research, advanced animal breeding, and rearing knowledge. In agriculture, techniques such as nutrient application to crops, genetic selection of crop strains, increased yield through the use of the plant, high-yielding variety seeds, growth enhancers, and pesticides, and the use of methods to improve soil health such as crop rotation have demonstrated to be critical enhancers in food and crop production.

Cloning of wildlife breeds, growth enhancers, vaccination, and animal science to prevent disease outbreaks in groups of confined animals and promote their productivity and growth have proven beneficial in increasing food production. Using growth promoters, vaccination, and veterinary medicine to stop disease outbreaks in herds of confined animals and encourage their productivity and growth are some techniques that have proven helpful in the animal breeding industry for boosting food production. The following are some of the causes to understand the wastage occurrence in the production phase of the food chain.

- Harvesting that is postponed or early due to a lack of knowledge about maturity indices, a concern for theft, labor scarcity, or other factors.

- Damage from heat, spills, and mechanical accidents due to poor harvesting techniques.
- Fungal infection during storage as a result of insufficient grain drying.
- Poor or ineffective selection of packaging materials and containers for the harvested products.
- Sanitation and hygiene regulations are not adequately implemented, especially for the product's packing and transportation containers.

1.2.2 Storage:

Storage is the practice of preserving the quality of agricultural products and halting their degradation for a predetermined amount of time after they have passed their expected shelf life. It is a tool for managing time, allowing delayed consumption, and producing marketing. Different crops are harvested and stored using other techniques depending on the final use. Several different storage structures are employed globally to store horticultural produce successfully. Fruits and vegetables, pulses and grains, and animal goods all require varied methods and means of storage because some are naturally more perishable than others. After harvest, the grains and pulses are often dried to remove any remaining moisture that could potentially enable the development of bugs and germs. After drying, these could be kept for a few months in an area with controlled humidity and temperature. Fruits and vegetables should be kept in a room between 0°C and 4 °C because they are often perishable by nature. It is essential to maintain this temperature to prevent the growth of microbes and enzymes that could harm the fruit or vegetable. The humidity in the space is also high to keep fruit and vegetables fresh. Generally, the makers must store high-quality products and keep the building cool. The following are examples to understand the wastage occurrence in the storage phase of the food chain.

- The improper storage of shelf-stable commodities, such as grains, leads to losses from pest infestation and fungus growth.
- Highly perishable food items like fruits, vegetables, fish, meat, and dairy lack adequate cold storage facilities.

- Due to the lack of accurate information regarding post-harvest treatments, insecticides, and dressings that would mitigate storage damage.
- The state of warehouses is terrible due to inadequate ventilation, sanitary conditions, gas composition, and illumination.

1.2.3 Processing:

The conversion of raw materials and intermediates into goods consumed by humans to enhance energy and nutritional availability, digestion, look, taste, storage stability, security, and dissemination is called "food processing." In this way, perishable things can be effectively stabilized and kept. The shelf-life of items is extended by preservation techniques like sterilization, pasteurization, and canning, which also helps to cut down on chain wastage. The food business has long been known for altering natural foods to make them more alluring or preserve them for a more extended period.

Processing becomes a crucial step, particularly in the meat industry, to maintain the flavor and quality of meat. The well-known preservative sodium nitrite is used in processed and refrigerated meats to prevent the formation of bacteria spores. In addition to beef, some other relatively necessary and often consumed food items are also processed. These products include cheese, bread, spicy nibbles, chips, pastries, cakes, and canned fruits and vegetables—examples where we can see the wastage due to processing in the chain.

- Defects come from processing errors that happen occasionally. The current processing facilities lack the necessary equipment to handle seasonal crops and vegetables.
- The packaging's quality is poor.

1.2.4 Distributing:

Food is typically distributed to the general public through food distribution. Food is often prepared, packed, transported, and delivered to a sales outlet to be sold at the retail market after being distributed in a manner that varies depending on the location. After a gradual shift from small outlets and farms to rapidly expanding large corporations, food is now distributed through chain stores, supermarkets, and retail cooperatives. Depending on the perishability and type of food, some are transported locally by cart to locations like the village market. In contrast, other food is transported long distances and placed into enormous freight crates. These are sent to a warehouse to potentially wait for weeks or even months in refrigerated trucks and railroad wagons. There is always a significant amount of risk that merchants and entrepreneurs take on when shipping food to distant locations, including worry about maritime dangers, damage to the cargo ship or transport vehicle, unanticipated accidents and eventualities, etc. Some of the examples mentioned below are about Distribution Wastage.

- Rough treatment during packing, loading, and unloading for transportation.
- Inappropriate transport containers or cargo.
- The lack of ventilation in vehicles.
- The lack of refrigerated trucks and the poor state of the roads.
- As a result of the off-loading locations' lack of refrigeration facilities.

1.2.5 Consumption:

Food consumption is the term used to describe the estimated amount of food that people can consume according to the FAO Food Balance sheet. A food balance sheet is a thorough inventory of the nation's food supply for a specified period. The total amount of food accessible in a given country for a certain period is calculated by adding the total amount produced and the total amount of food imported, then adjusting for any remaining supplies already present in the country.

The food balance sheet includes information about the supply, feed, calories, fats, waste, and other characteristics of food. A nation's total availability and food security are assessed after integrating and comparing all these factors. Because of food loss at multiple stages of the food cycle, the amount of food supplied is typically expected to be more than the volume of food digested. Food is lost and wasted at the industrial, agricultural, and domestic household levels. Food is wasted at the production, storage, and distribution levels because the product may be exposed to unfavorable temperatures, bacteria, or enzymes that could hasten its decomposition; however, in households, food is wasted most frequently by being thrown away, fed to pets, burned, or allowed to rot. Typically, people buy food for domestic use from the closest retail stores. However, in particular large cities, some department stores hold bulk inventories to sell to the public. In addition, eateries like cafes and restaurants often serve baked and prepared cuisine. Guests are provided with predetermined menus of food items at some ceremonies or events, as specified by the host. There are countless ways to waste food, whether raw or cooked. Thus, the main remark that can be made about these three categories as a whole is that none of them are immune to it [FAO 21].

At the home level,

- leftovers from over-preparation.
- Due to flavor, leftover food is not being used.
- Food is not eaten promptly.
- Unexpected purchases.
- A lack of information about consuming food more effectively reduces food waste.

In hotels and restaurants

- The large serving sizes of the cuisine.
- Buffet style.
- Unexpected meal orders.
- Consumers are not permitted to take "leftover" food home.

Miscalculation of invitees at social gatherings or public events

- extravagant display of money because of social standing
- There are too many dishes on the menu.
- A variety of cuisines

1.3 Effect on the Environment due to Food Waste

The waste of food leads to inefficient use of resources and has negative impacts on the surrounding environment. Between 2012 and 2050, an expanding population and rising wealth are expected to boost the demand for agro-products by 35 and 50 percent, exerting even more significant strain on the planet's natural resources [62]. This emphasizes how critical it is to minimize food wastage and loss. Even though more meals are delivered to users for a similar level of resource use, lowering waste production will constantly improve productivity and sustainability, irrespective of the environmental purpose. These reductions always lead to lower Greenhouse gases per calorie consumed. Utilizing resources more accurately and cutting methane emissions per pound of food will be critical to meeting rising demand in the setting of a more significant, wealthy population in a sustainable manner.

Agriculture consumes the vast majority of the world's available freshwater resources. These freshwater resources are fast decreasing, which coincides with a rise in demand brought on by the millions of people worldwide who are both hungry and thirsty. A substantial amount of water is used in food production at every stage, whether it be by irrigation, spraying, pouring, or one of the many other techniques. In addition, water is essential for feeding fish, poultry, and animals. As a result, not only do we throw away food, but we also throw away millions of gallons of water, which is required for the cultivation and maintenance of plants. However, improved performance sometimes translates into reduced resource consumption or GHG emissions. There are two types of land waste related to food waste. The property is utilized to both grow food and dispose of leftover food. Arable and non-arable land are the two types.

The area of land used for agriculture globally is approximately 11.5 billion hectares. Crops can be cultivated on arable land, preferable to non-preferable ground growing crops. These uncultivated plains are ideal for raising livestock. Animals are kept on about 900 million hectares of non-arable land to produce meat. There is no issue with the ground used to raise livestock or crops. Wasted food is the real issue. We never really realize what we waste when we throw away food. The total environmental effect will be evaluated by price changes caused by reduced food consumption and waste, which will implicitly define its influence on natural resource usage and GHG emissions. Customers might want more of a product, for instance, if the price of the product decreases due to the increased supply brought on by lower losses. This will balance out the environmental benefits of the increased food system efficiency and less food loss. Toxic waste, constraints on land, and strains on aqua resources are the three primary forms of ecological legacies of waste and lost food that are commonly quantified. These, in turn, may have an impact on biodiversity. For using food loss decrease as a way to achieve the sustainability objectives entrenched in the SDGs [UNEP 2021], it will be necessary to understand precisely where in the food source line the loss or waste occurs, what kinds of goods are implicated, which ecologic impressions are impacted, and how the expenses of trying to intervene to decrease the loss or waste are. In recent years, there has been a growing interest in food waste by international organizations, non-governmental organizations (NGOs), local, national, and European governments, and academics from various disciplinary fields. Growing worries about environmental effects, such as resource depletion and food security, attention to the issue has increased due to exhaustion and carbons linked to food garbage. Due to these expanding environmental, social, and economic issues, food waste is becoming more pressing for businesses, governments, academics, NGOs, and the general public. Growing evidence shows that food waste along the food manufacture-depletion cycle is increasing. Encourage or discourage behaviors that result in food waste. An exhaustive study of families gives insight into the depth of the issues surrounding the waste of food and practices that promote sustainable eating habits. Due to the issue's complexity, the data about the factors that lead to food waste and the barriers that prevent its elimination are still scattered. While analyzing the causes that lead to food waste, particular attention is paid to the political, economic, geographic, and cultural characteristics of the United States. On the other hand, there hasn't been comprehensive research that investigates and charts in great detail the intellectual landscape of the major factors that contribute to food going wrong at home. Instead of worrying about the implications of waste food on the environment and society, these feelings of guilt are motivated mainly by personal difficulties such as a loss of financial stability [62]. Although research has shown that people with children in their houses are likely to waste more food than those without children and that persons over 65 tend to waste less food, socio-demographic characteristics are less predictive. Larger homes squander less per person, whereas single-person households waste the most. Aversion to consuming leftovers, improper storage practices, confusion about food shelf life and data labeling, and provision are a few more common causes of throwing away excess food while highlighting the methods people can take to restrict food waste in their homes. Infrastructure like storage and shopping centers remarkably impact how household food is handled. The fact is that practices for reducing food waste, like shopping or cooking with less energy, have all been hindered by a perceived lack of time due to today's typical scheduling of work, family, and free time. However, little study has been done on how people's wasteful behaviors are influenced by their perceptions of their time availability. The relationships between shifting patterns of work and leisure and consumer food waste must be considered if we approach the difficulty of wastage of food methodically. This is true even though having more information about food storage options and their shelf life is advantageous. We strongly advocate for studies that, instead of only examining attitudes around food waste, adopt social practice ontologies that may provide insight into the practices and daily activities that characterize domestic life food loss utilizing various data collection techniques, such as composing interviews with observations is crucial to document actual events and give a complex description of how and the reasons food is squandered [62].

1.4 Goal of Food Waste Reduction

- Between the farm and the fork, one-third of all food is lost or discarded, and the COVID-19 epidemic is making this problem more complex along the entire food value chain.
- By reducing its national post-farm gate food loss and waste levels by 27% from 2007 to 2018, the United Kingdom became the first to reach this goal more than halfway. This indicates that achieving the goal is both doable and advantageous. The world is drastically behind where it should be, with only ten years left. If SDG (12.3) is to be accomplished by 2030, it must be. More organizations and governments must actively pursue the Set goal to reduce food waste using the Target-Measure-Act strategy.

- SDG 12.3-aligned objective, track food loss and waste to identify hot places, track development, and take decisive action to cut down on food loss.

- The loss or waste of almost one-third of the food produced worldwide has a hugely adverse effect on the environment, the world economy, and human livelihoods and well-being.

- The COVID-19 epidemic has made it even more urgent to discuss food systems that have found it challenging to adapt to unpredictable swings in demand, workforce shortages, and declining disposable incomes during the past year.

- Given that particular nations have observed less domestic food waste under lockdown, the pandemic may also have some lessons to teach us about handling consumer in-home waste.

- The mitigation of climate change, the enhancement of food security, the reduction of prices, and the reduction of strain on resources such as land, water, biodiversity, and waste management systems are only some of the advantages that accrue to people and the environment when food waste is reduced. Nonetheless, this potential has, regrettably, not been fully utilized as of this point in time.

- Because the actual scope of food waste and its effects are not well known, this possibility may have gone unnoticed. Few governments have reliable statistics on food waste to support their actions and determine where to focus their efforts [SDG 12.3 2020 Progress Report]. The extrapolation of data from a few nations, frequently using dated data, has generated global food waste estimates.

1.5 Challenges

A 1/3rd of all food produced worldwide by the Organization of the United Nations needs to be recovered or squandered (FAO 2011). This extreme degree of inefficiency has detrimental effects. Think about food safety. Food losses close to farms are expected in some locations, making it difficult for farmers to make a living and occasionally feed their families. In other regions, such as North America and Europe, food waste near the end of the supply chain can impact spending and household nutrition. Wherever food loss and waste happen, the reality that more than 1 billion tonnes of food are wasted in a globe where one in 9 people are malnourished is alarming. Now more than ever, the world has to maximize what is already cultivated as food consumption rises to satisfy the demands of a growing population. Think about the surroundings. Farming uses about one-fourth of the water yearly to produce food that is eventually wasted or lost [62]. Every year, it is necessary to cultivate food on more land than China's size due to food damage (FAO 2013). Additionally, it produces around eight percent of the global annual carbon emissions (FAO 2015). To put this into perspective, consider that food loss and waste would be the world's third-largest producer of carbon gases behind China and the United States. Although the concept of food loss and waste seems straightforward, no universally accepted definition exists. The multiple purposes frequently reflect the numerous issues analysts concentrate on or link to food loss. Accordingly, the lack of a uniform definition makes it difficult to analyze the spoiling of food items. The terminologies used in this study are the product of a consensus established after discussion with specialists in the field. Although helpful in measuring environmental effects, this assessment ignores the excellent value of various items and runs the danger of giving low-value goods a higher weight just because they are heavier. Any reduction in financial costs and advantages should be considered when developing interference and strategies to decrease the waste of food. This is acknowledged in the report by using a metric that considers the product's economic value. Consumer food waste is a problem that has primarily been mentioned and connected with high-income nations. However, this issue is one that the growing economy encounters more frequently. Food waste is inversely correlated with household affluence. Over the past few decades, rising wealth, demographic shifts, and cultural shifts have caused changes in eating behaviors that frequently favor convenience.

1.6 Considerations of Food Waste from Around the World

Food waste is an international issue. Governments worldwide enact new rules, define goals, and organize campaigns to reduce waste. The following statistics and facts illustrate how much food is wasted globally [13][1].

a) 1.6 billion tonnes of food are wasted globally, which might be fed to the hungry and help reduce the number of people going without food.

b) Every year, 3.3 billion tonnes of carbon dioxide are emitted into the atmosphere due to food waste, endangering the ecosystem and contributing to global warming.

c) Besides the food waste, which is almost three times as much as a large lake, water waste as a critical source for food production is also a problem.

d) Food is wasted with the land used to produce it, which amounts to about 140 million areas of land, or 28% of the global agricultural land.

e) The food industry is a significant part of carbon gas emissions, including methane from landfills where leftover food is dumped.

f) The local collection authority might divert up to 100 kg of food waste per family annually by collecting leftover food from homes.

g) Food loss during Agri production is a significant issue in underdeveloped nations, particularly at the buyer level, which tends to be higher among middle-class and high-income families.

h) The yearly economic loss caused by food waste is estimated at around $750 billion.

1.7 International Initiatives to Reduce Food Waste

Many nations have concentrated on raising consumer knowledge of the value of decreasing food wastage has become more widespread over the past few decades. Several instances of them are:

1. "Empty Plate" Campaign in China – This campaign aims to raise awareness of food waste among the general public. Initially, this task focused on public food consumption, gatherings, and banquets. Since the program's inception, there has been a notable decrease in food waste at restaurants thanks to public media mobilization, programs at the federal, state, and local levels, the installation of CCTV at the provincial level, and several general commercials against food waste [14].

2. Republic of Korea: "Half Bowl" Campaign and New Container - This campaign urges locals to order half of a rice bowl's recommended serving size to prevent food waste. 20% less food wastage in restaurants was anticipated. Further initiatives were launched, such as the food container, which adds a layer to block air and moisture and prevent early decomposition [15].

3. Japan: Delivery Date Extension Experiment - Japan is the only nation that has begun an experiment to extend delivery dates to reduce food waste by sending goods at least one-half an hour before their expiration time or date. They used the "1/3rule" calculation to carry out this concept, which states that food products should not be distributed to merchants if they are more than one-third past their expiration date [16].

4. Love Food Hate Waste works with partners like us to give citizens the ability to lessen this significant contribution to climate change. It's an area where we may significantly improve things by making minor adjustments. In the UK, people waste 70% of their food that goes to waste in their own homes. Every year, 4.5 million tonnes of food that could have been consumed are wasted. The power is in the hands of citizens, and we can help empower people to utilize it to significantly reduce the quantity of food wasted in the UK [17].

5. Stop Wasting Food - Food waste is still a significant issue in Denmark. According to the number of completed events and initiatives along the entire value chain from farm to fork, the amount of Danish and international media mentions, and the number of followers on social media, we are Denmark's most significant movement against food waste. We raised awareness of food

waste in Denmark and highlighted its efforts to combat it internationally. A non-profit consumer movement called Stop Wasting Food works to reduce food waste. Since 2008, it has helped to increase awareness of the issue in Denmark and has collaborated with the EU, the Nordic countries, and the UN to accomplish several notable outcomes. We are working to reduce the hundreds of thousands of tonnes of food waste Denmark produces yearly. Many thousands of Danes and a sizable number of influential top lawmakers and well-known culinary personalities support us in our fight against food waste [18].

6. USA: The U.N. Food and Agribusiness Association gauges that 130 million tons of food are lost yearly. The US squanders more food generally than the Unified Realm, Italy, Sweden, France, and Germany consolidated, as per the Barilla Place for Food and Sustenance. Tragically, a few nations are more terrible wrongdoers than others. The United Nations Environment Program found that the global food production business is responsible for 70 percent of the world's consumption of freshwater and 80 percent of the destruction of forests. Food production is the single most important factor in the decline of biodiversity and is responsible for at least 30 percent of the world's total emissions of carbon dioxide. To kick off this week, we have provided a list of 21 organizations that are actively working in farms, institutions, restaurants, and other venues to conserve the time, effort, and resources that go into the production, processing, and marketing of food [19].

7. Spain: To decrease food waste, the Ministry of Agriculture, Fisheries, Food, and Environmental wants to implement the More Food, Less Waste plan. The approach focuses on raising awareness and measuring waste at every food chain level. The Ministry of Agriculture, Fisheries, Food, and Environmental introduced a new strategy called The Circular Economy Strategy, including production, consumption, waste management, and water reuse as its key lines of activity [21].

According to a researcher, the importance of food and the necessity to address the issue of widespread hunger and malnutrition are shifting perspectives across the globe. Due to this growing realization, several countries worldwide have implemented several steps in the shape of laws, legislations, punishments, and policies to stop food wastage and its avoidable loss. Overall, we note that research on household food consumption. The increasing number of studies show that understanding trash in homes is advancing. Several authors have pointed out that the development of food waste at the household level is a complicated and diverse problem caused by various factors and behaviors. To start With, it has been revealed by our data that households are generally worried and feel bad about wasting food.

1.8 A Nationwide View of Food Waste

In FY2014, after harvesting, losses in India were predicted to cost USD 1519 million, a sizable loss to the country's income [21]. However, India is only ranked 94th out of 107 nations in the 2020 Global Hunger Index. Given the current health and economic crises, the pandemic-19 highlights the reality that food scarcity still poses the most significant challenge in India. As one of the world's top food producers, India is predicted to have a very high carbon, water, and land footprint due to damaged and wasted food. India still needs to establish a target that is in line with SDG 12.3 or start to report on it. India is one of the few nations that has conducted multiple country surveys coordinated by the Indian Council of Agricultural Research (ICAR). Furthermore, numerous infra-national studies and international organizations have to calculate the postharvest losses of particular crops at particular food chains. However, the subject of such investigations has yet to be food waste measurement. The authors thoroughly assessed the literature on food loss and waste in India to give information on its extent, the effects on social, economic, and ecological systems, and potential solutions. One of the few nations, India, has done two thorough nationwide surveys on food waste in the past ten years. Since 1968, when the Panse Committee revealed 9.33 percent losses in some food grains, the Union Government has taken the lead in assessing post-harvest losses. In a thorough sample survey conducted between 1973 and 1974 by the Directorate of Marketing and Inspection of the Ministry of Agriculture and Farmers Welfare, food grain losses were estimated to be 5%. (2001 Rajya Sabha, Parliament). The issue of food loss in India needs to get more attention. Increased attention to the problem could positively impact India's food security and other issues [21].

1.9 Preventive Measures on Food Waste

- Cooperation among farmers may lower the danger of overproduction. Transferring surplus crops from one farm to another aids farmers in finding solutions to the issue of crop shortages. Poor farmers may occasionally harvest their crops early due to a lack of money or food scarcity in the middle of the growing season. Premature harvesting can sometimes cause developing countries to lose food; some wealthier nations also experience this issue.

- To prevent the product from being rejected by consumers, the farmer can sell the produce directly by going to the markets or opening farm shops. Food is left because stores have quality standards based on weight, size, and appearance. Direct sales by farmers are preferred to lower the amount of crop rejection.

- Road, energy, and market investments can all help to strengthen infrastructure. Private sector investments can then be requested to upgrade the cold chain and storage infrastructure.

- Before going out to buy food, we should ensure that enough food in the pantry, the freezer, and the refrigerator. Create a weekly inventory of what needs to be used up, and use that information as the foundation for our meal planning.
- When grocery shopping, users should schedule their meals for the upcoming week and only buy what they require.

- The user should generate a shopping list based on the number of meals they want to consume at their residence. Consider how often they will eat out, whether or not they will utilize frozen ready-made meals, and whether or not they will use any of our leftovers in any of the meals they prepare for us.
- It is recommended that the refrigerator's high-humidity tray be utilized for most vegetables, particularly those more prone to wilting.
- As bananas, apples, pears, stone fruits, and avocados ripen, they emit ethylene gas, which causes other produce to ripen and perhaps spoil more quickly. This is especially true of apples and pears. Store these in a separate location from the other food items.
- If we want to prevent germs from growing on the berries, cherries, or grapes, wait to wash them until just before you plan to consume them.
- When storing some crops, such as potatoes, eggplant, winter squash, onions, and garlic, it is essential to do so in a location that is cold, dry, dark, and has adequate ventilation.
- Grain should be stored in airtight containers clearly labeled with the contents and the date.
- Visit the freezer and make good friends with it. Freezer space should be utilized for foods such as bread, sliced fruit, meat, and any leftovers likely to go uneaten. Include the date and a description of the contents on the label.

1.10 Deep Learning Technique

Unofficially known as "deep learning," this collection of machine learning methods often consists of multi-layer neural networks. The rise of high-performance computing resources led to the popularity of deep learning methods that use these networks. Low-level features are extracted by the first layers and combined with later layers to create a comprehensive representation. Algorithms based on deep learning employ more layers than machine learning algorithms do.

The term "deep learning" refers to a family of computational methods that include the recent proliferation of large, high-quality, publicly available labeled datasets and various learning algorithms. The majority of deterministic deep learning-based models are currently available in the literature. The future is unpredictable, but there are some occasions where a deterministic prediction might be sufficient. For instance, just a tiny portion of a car's travel is surprising; the majority is pretty deterministic. However, a deterministic model will learn to average between all the potential outcomes when many predictions are equally likely to occur. Deep learning marks the start of a fresh era of artificial intelligence research by requiring the creation of complex, multi-layered neural network models; the use of a vast amount of training data; the employment of a large number of computer resources; and, finally, an understanding of how to extract multi-level abstract features from data. Because of the complicated nature of the deep neural network method, the large number of iterations, and the high complexity of the computation, there are several challenges and bottlenecks associated with deep neural network parallelization.

The correctness of the algorithm is the primary concern while developing a deep learning algorithm, and parallelism is not a significant consideration. As a result, multi-core processing capabilities can only be utilized partially by current deep learning techniques. There are four different model compression strategies. Pruning is one of the categories. The neural network is mainly connected by nodes of one layer and one layer, with some weight on either side. Pruning entails the removal of edges that may not be important if we discover that some sides have modest consequences. Edges with smaller weights can be seen after training the large model. Retrain the model using the reserved edges after removing those edges. By sharing weights, the model can also be compressed. Assuming that there are complete connections between two neighboring layers and that each layer contains 1,000 nodes, there are 1,000 × 1,000 nodes between the two layers or 1,000,000 weights (parameters). Through this dual process, we can gather feedback data from unlabeled data, determine how well our model performs, and then train and update the model in response to the feedback data. To achieve the goal of learning from unlabeled data, reverse the model. In learning and training, hyperparameters are predefined neural network parameters. These factors significantly impact the neural network, and the difference is vast. Deep learning requires much hyperparametric tuning. With the most in-depth knowledge of deep understanding and neural networks, hyperparameters are likely to impact a network's performance. Suppose enough of these models can learn complex functions through transformations and buildings. For instance, the features used in the categorization task that are crucial for discriminating are typically kept from, while unimportant variations are represented at higher levels of representation. The main benefit of deep learning versus conventional feature selection procedure is that it is carried out automatically by an overall learning process without human intervention. The depths of their specific hierarchical learning and deep learning techniques have shown excellent results in finding the high-dimensional data's structure in many domains. Many issues in computer science and machine learning cannot be reduced to a simple algorithm that can be solved. The answer to those difficulties must be dynamically adjusted for each case in which the algorithm is used. Human brains can adapt, but there is no straightforward way to write adaptable computer code. Because of its capacity for generalization, our brain can reason deductively, which is the first step in learning.

The future of AI has been transformed by deep learning. In the early 1980s, much research was being done on artificial neural networks and other newly developed approaches. However, they could only have structures with one or two layers because of the need for more processor speed and memory, which led to less-than-amazing outcomes. Now that computers have greater RAM, CPU, and GPU power, developing and testing more profound and complex designs is possible. During the past several years, there has been a fast development of various deep architectures with various learning paradigms. In this investigation, we categorize different types of food waste by employing a deep convolutional neural network strategy. Deep neural networks, comprised of tens of layers of convolutional data, are taught specific tasks by being trained on data that has been tagged. The labeled training data contains several thousand input and output pairs for further analysis. During the training phase, the networks acquire the skills necessary to create the predicted training output given the training input data. Millions of parameter values for feature extraction convolutional filters are computed throughout the training process. In image processing, trained deep convolutional networks' first layers look for essential features like edges and corners. Gathering practice material for object detection network training Moreover, segmentation networks are costly. The subfield of machine learning, known as deep learning, is essential. In comparison to more traditional ML approaches, DL algorithms provide several benefits when it comes to the categorization of images, the recognition of objects, and the discovery of patterns. Extraction and selection of distinguishing features using machine learning approaches might be challenging to accomplish because weeds and crops can have comparable appearances methods can solve this challenge effectively based on their feature learning capabilities. Recurrent neural networks operate well for time-series media analysis like videos and audio. A very slight discrepancy between the new data generated by generative adversarial networks and the input data's statistical similarity.

1.10.1 Role of deep learning in Food Waste Management

The capacity of CNN to extract features for improved image categorization makes it the best option among these three supervised deep-learning techniques for detecting apple fruit disease. The deep learning techniques use convolutional neural networks (CNN). The two-dimensional data representation in this format can be advantageous for convolutional networks. A deep neural network model comprises a complex web of hidden elements. Convolutional networks, which benefit from the advantages of both designs, can be created by combining deep networks. The three main layer types that make up a convolutional neural network are the Pooling layer, SoftMax, and Convolutional. The input picture is processed using several kernels within the convolutional layer. The feature map size can be reduced by utilizing the invariance average included inside the pooling layer. The pooling layer and the convolutional layer are the two components that make up the feature extraction module. The input feature maps are organized into class values by the Softmax activation function located in the Softmax layer. To generate extra outputs of feature maps, they carry out feature mapping while they are still in the process of convolving the entire picture using a variety of kernels at intermediate stages. Following the conventional placement of the convolutional layer is the subsampling layer, also known as the pooling layer. This layer is responsible for downsampling the feature map. The downsampling layer serves two primary purposes: a) reducing the feature map's dimensionality and b) keeping some of the feature's scale-invariant properties. That is a process; a uniform grid is used first to partition the feature map into several spatial sections. These regions might overlap in certain places, and the output is then determined by each image section's average or maximum value. The study that has been done up to now has shown that when it comes to extracting picture features, the performance of the ultimate pooling operation is better than that of the average pooling. After connecting with a variety of convolutional and subsampling layers in an alternating fashion, the convolutional neural network employs a fully connected network to classify the characteristics that have been retrieved. The generation of an input-based probability distribution is now possible due to this. The goal of the training phase of a convolutional neural network is to bring the loss function of the network down to a lower value. The weight-sharing feature of CNN, which reduces the network's total number of trainable parameters, is one of the primary reasons to use it in this scenario. This feature assists the model in avoiding overfitting and increases generalization by reducing the total number of trainable parameters.

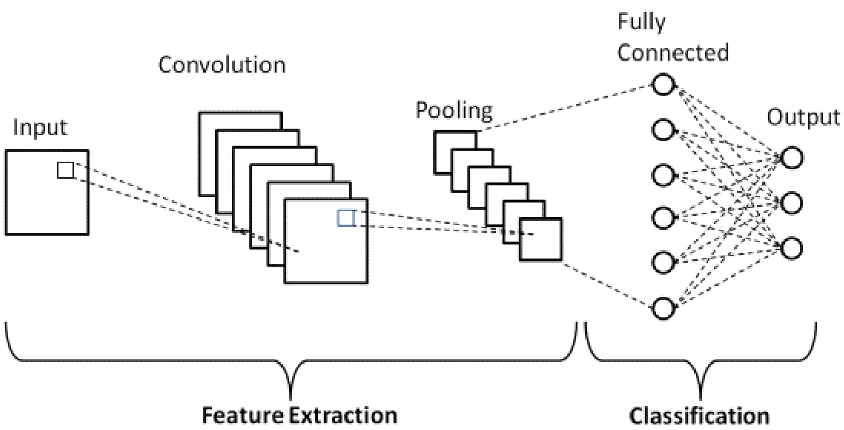

Figure 1.4 CNN Basic Architecture

1.10.2 Convolution Layer

Currently, the feeding photos are being examined to extract their various attributes. The mathematical convolution with the input image is performed in this layer using an NxN filter of a specific size. We may see a particular filter's impact on a photo by sliding the filter over the input (N, N). As a result, information about the image, such as its corners and edges, is included in a feature map. This feature map is the starting point for subsequent layers to learn new picture qualities. The pooling, Softmax, and convolutional layers are three fundamental layers that make up a convolutional neural network [Figure 1.4]. These allow for successful classification and the resolution of several issues relating to food waste. The convolution operation can be calculated by using the below-mentioned formula:

$$k_j^l = f\left(\sum_{i=1}^{P_j^{l-1}} D_{ij} * x_i^{l-1} + b_j^{l-1}\right).j = 1,2, \dots .M \tag{1.1}$$

where M represents the number of feature maps in the convolution layer, x^{l-1} i is the upper layer feature map, Dij indicates the offset of the jth convolutional kernel of the current layer, P_j^{l-1}reflects the feature maps in total, and f(.) is the activation function. k_j^l identifies the convolutional layer's jth feature map.

1.10.3 Pooling Layer

A method known as layer pooling may reduce computation costs and avoid overfitting by lowering the output of the convolutional layer. The most often used pooling techniques are those based on average and maximum pooling. This investigation's maximum pooling downsampling method allowed the algorithm to converge quickly. A 2x2 subsampling frame is used in each of the pooling levels. where j stands for the jth feature map after pooling, k_j^l stands for a convolutional layer to the sampling layer window size, $\sum_{i=1}^{P_j^{l-1}} D_{ij}$ represents the downsampling process, and f() is the pooling function.

$$k_j^l = f\left(1/n \sum_{i=1}^{P_j^{l-1}} D_{ij} + b_j^l\right) \tag{1.2}$$

Alternating links connect convolutional and pooling layers. The total number of feature maps returned rises as network depth climbs while the size falls. The characteristics that were eliminated have a more comprehensive range of complexity.

1.10.4 Fully Connected Layer

Complex cognition in neural networks is made possible by fully connected layers. Although they are no longer visible due to the convolution and pooling layers, they are still there. Before the completely connected layer, the inputs and outputs are entirely coupled. The 2D feature map is transformed into a classifiable 1D feature vector by the fully linked layer. To establish the connection layer, we utilize the following formula:

$$O_{c,e(x)} = f(c_x^T + e) \tag{1.3}$$

In this instance, f(.) represents the activation function, c represents the weight vector, x indicates the input eigenvector, and represents the offset subscript. $O_{c,e(x)}$ indicates the neuron output. The network can generalize more effectively and avoid overfitting by cutting off a set number of neurons after training.

1.11 Applications

We cover some critical applications where CNN is used to achieve cutting-edge performance, such as image classification, word recognition, action recognition, object detection, human posture estimation, and picture captions.

1.11.1 Image classification

CNN has improved classification accuracy thanks to several characteristics, including weight sharing and several levels of feature extraction, including classifiers. Compared to other techniques, mainly when dealing with massive datasets. The creation of AlexNet in 2012, which went on to win the ILSVRC challenge that same year, marks the first advancement in picture categorization. After that, researchers continued to improve the CNN model, elevating it to the top of the list for image categorization issues [67].

1.11.2 Text Recognition

Much study has been conducted on the topic of text detection and identification inside photographs for a considerable amount of time. CNN's first pioneering contribution in this field is the artificial intelligence system known as LeNet-5, which successfully identified the data included in the MNIST dataset. In recent years, CNN has been a key contributor to different breakthroughs in the process of detecting the text (digits, alphabet, and symbols belonging to many languages) contained inside a picture [60].

1.11.3 Action Recognition

Several efficient CNN-based approaches can now accurately predict human subjects' actions or behavior based on the visual appearance and motion dynamics of any human body. In terms of AI, this propels CNN to the following level. It entails identifying action in still photos or a video sequence.

1.11.4 Medical Image Analysis

CNN is rapidly establishing itself as a foundation at the forefront of medical innovation as a result of its enhanced ability to diagnose illnesses through the processing of medical images such as MRI scans, X-rays, and other imaging modalities. Nowadays, CNN-based models are capable of effectively diagnosing a variety of medical problems. These disorders include diabetes, Parkinson's disease, brain tumors, pneumonia, and breast cancer.

1.11.5 Security and Monitoring

The ability to discover or identify offenders even in complicated situations is now possible thanks to security systems with computer vision capabilities that constantly monitor homes, metro stations, roadways, schools, hospitals, and many other locations.

1.11.6 Automatic colorization of image and style transfer

CNN is rapidly establishing itself as a foundation at the forefront of medical innovation as a result of its enhanced ability to diagnose illnesses through the processing of medical images such as MRI scans, X-rays, and other imaging modalities. This improvement in CNN's ability to diagnose illnesses is because CNN has improved its ability to diagnose illnesses through the processing of medical images. In today's world, models constructed with CNN data are capable of accurately identifying a wide range of medical conditions. Diabetes, Parkinson's disease, brain tumors, pneumonia, and breast cancer are some of the diseases that fall within this category.

1.11.7 Satellite Imagery

Today, CNN plays a significant part in helping to identify various natural disasters like hurricanes, floods, landslides, and tsunamis. We can use satellite image analysis to create innovative city plans, extract roads and rivers, classify land, identify crop patterns, stop deforestation, etc.

1.12 Deep learning frameworks

Without getting into the specifics of the underlying algorithms, a deep learning framework aids in more quickly modeling a network. Every framework is designed differently for every function. Deep learning models can be learned parallel using relevant open-source frameworks that businesses and academics have developed. The DNN library is supported on the GPU to speed up the network. High-performance multi-threaded libraries are used on the CPU to train the network utilizing data parallelism or model parallelism. Model or data parallelism is employed for implementing distributed parallel deep learning models. The following list of software tools is typical usage:

1.12.1 TensorFlow

TensorFlow is an open-source software tool that is used to calculate numerical problems by making use of data flow graphs (TensorFlow 2018). The distributed architecture of TensorFlow contains components such as the distributed master and worker services along with kernel implementations. The mathematics, manipulation of arrays, control flow, and state management tasks are all covered by these 200 standard operations, which have been developed in C++. TensorFlow may be utilized at any stage of the system development process, including research and development, and production. It can function on computers with a single central processing unit (CPU), graphics processing units (GPUs), mobile devices, and massively distributed systems with many nodes. A "flow" is a calculation that is based on a data flow graph, and a "tensor" is an N-dimensional array. Both of these terms relate to the same thing. During the process of TensorFlow, tensors move from one end of the picture to the other. TensorFlow is a framework that allows complex data structures to be sent to an artificial neural network so that they may be evaluated and processed.

1.12.2 Keras

Keras can perform faultlessly on GPUs and CPUs, provided that the underlying frameworks are adequate, and it is compatible with Python versions 2.7 to 3.6. Keras is an application programming interface (API) that was developed to be both user-friendly and simple. By offering APIs that are stable and easy to use, Keras abides by best practices for reducing the amount of mental strain that developers experience. Modularity, A model is a collection of fully independent, fully modifiable modules that can be coupled with the fewest number of constraints feasible. In particular, it is feasible to combine neural layers, cost functions, optimizers, initialization methods, activation functions, and regularization techniques to construct new models and integrate existing ones. The introduction of new modules into existing ones provides a variety of examples that make it simple to limit expressiveness. Using Python to write code results in work that is concise, easy to debug, and scalable. Because of this, model descriptions may be created.

1.12.3 PyTorch

PyTorch is the name of a Python package for GPU-accelerated deep learning (PyTorch 2018). Torch makes use of the library, which is an optimized C library that also provides a Python interface. The Artificial Intelligence research team at Facebook has been working on it since 2016. PyTorch is created with the programming languages Python and C, as well as CUDA. Acceleration libraries developed by firms such as NVIDIA and Intel MKL have been incorporated into the library. The tensor and neural network backends (TH, THC, THNN, and THCUNN) for both the central processing unit (CPU) and the graphics processing unit (GPU) are the primary components of this system. Both deep neural networks (DNNs) are constructed on a tape-based auto-grading system, and PyTorch has tensor computing capability with substantial GPU acceleration. It has gained popularity because it makes it simple to construct complicated architectures. Usually, altering a network's behavior necessitates starting over. Reverse-mode auto-differentiation, a method used by PyTorch, enables easy modification of a network's behavior. Both the scientific and business communities use the library. Pyro is a general-purpose probabilistic programming language developed by an Uber engineering team using PyTorch as its backend. Facebook, Twitter, NVIDIA, and numerous more companies sponsor the library, which is open source and available for free under a BSD license.

The thesis is organized into a total of six chapters Introduction of the chapter is covered in Chapter 1, the Literature review is discussed in Chapter 2, the Single Proposed Model is discussed in Chapter 3, the Ensemble Proposed Model is in Chapter 4, the Results and Discussion is mentioned under Chapter 5 and the Conclusion and Future Scope of the work of the thesis written in the final chapter 6.

1.13 Summary

In this chapter, we have discussed the introduction of food waste and the technology used to implement it further in the research. Food waste is becoming very particular and challenging in the coming days due to increased food scarcity. As we know, the population is the central issue in the country because of the difficulty in food availability for all the people. The country reports also say that we should be cautious in feeding food to all the people in the future. Because of all the above issues, we need to show special care for food waste at different stages. At the same time, technology is required to improve food availability and reduce food waste in different situations like retail, packaging, household, etc. The concept of deep learning plays a vital role in detecting the damaged and fresh by using convolutional neural networks. Nowadays, all the researchers are utilizing Convolutional Neural Networks for classification purposes.

Chapter 2

Literature Review

This chapter covers a deeper study and analysis of different techniques used by different authors in detecting fresh and damaged fruit using deep learning techniques to safeguard food wastage. A literature Review has been done for a couple of months through various papers and considered papers to analyze and to know the current and previous work related to our problem in this study. The result of different researchers who used a variety of approaches for detecting fresh and damaged fruit or food is elaborated on effectively and efficiently in this chapter. The researchers identified several holes and tried to close those gaps through their research. Below are some explanations of some of the researchers' works considered for this thesis work.

Jahanbakhshi et al. [23] suggested a Deep Convolutional Neural networks (DCNN) model for classifying sour lemons fruits. The CNN results were improved using a stochastic pooling mechanism and data augmentation. The local binary patterns and histograms of oriented gradients extract the features. Both healthy and damaged sour lemon fruits were classified using DCNN, and the implementation code was simulated using MATLAB R2016a Software. However, this model needed to extract the characteristics of quality and geometric agricultural products.

Unal et al. [24] introduced a convolutional neural network (CNN) to detect and classify fruits. Image pre-processing was performed to remove the image noises, and the classification was performed. Based on the embedded system, the real-time implementation was executed in the NVIDIA Jetson Nano board with the Keras platform. There were two different datasets with 20 fruits taken, and the experimental outcomes delivered higher, but it demonstrated higher cost and complexity.

Altaheri et al. [25] suggested CNN-based ALEXNET architecture to classify the date fruit. Based on pre-trained models, fine-tuning and transfer learning uses Deep Convolutional Neural Networks (DCNN) in fruit classification models. Generates a date fruit bunches dataset in an orchard that includes over 8000 pictures of 5 different date kinds at various maturity and pre-maturity stages to build a stable vision system.

Huge variations degrees are present in the dataset, which reflects the environmental conditions of date fruits like date bunches covered by bags, illumination conditions, scales, and angles. Nvidia GeForce GTX 1060 6 GB with one GPU train the CNN models, and Matlab2018b was used as the implementation software. It demonstrated higher accuracy rates and minimum execution time with higher feature dimensionality.

Bhargava et al. [26] suggested combining various methods like Artificial neural networks, K-nearest neighbors, Sparse representation classifiers, and Support Vector Machines (SVM). The split-and-merge algorithm detaches the image backgrounds and extracts RBG image values. The geometrical, textural, statistical, and color features were removed. By considering different k values, k-fold cross-validation evaluates the system performance. This model provided maximum accuracy and better-quality evaluation outcomes based on the experimental studies, but many fruit images affected the overall system performances.

Ashraf et al. [27] introduced convolutional neural networks (CNN) to classify the qualities of the fruit. Often these supermarkets and fruit distributors rely on human checking to ensure the quality of the fruit in one 's stock. Based on an input image, fruit is rotten or fresh was determined and the fruit image dataset trained the CNN model. By applying transfer learning, the Inception V3 model built the initial model. It delivered minimum cost, low dimensionality, and better probability score but the difficulties in feature extraction steps.

Singla et al. [28] suggested pre-decided grading criteria for the fruit texture analysis and deteriorated classification of fruits. The morphology, texture, and color features were extracted, and the overripe fruits were classified. The fruit grading and threshold model was used for segmentation. This model will significantly benefit the corporate fruit world by automating the selection process of fresh fruit. The overall system performances of this model enhanced the speed of fruit quality selection and demonstrated more significant computational difficulties.

Perez-Daniel et al. [29] suggested A stage object detector-based RetinaNet model for detecting rotten fruits. Depending upon the top of a backbone, multi-scale convolutional feature pyramid network computing demonstrates RetinaNet stages. The highest accuracy for fruit and rottenness detection was determined, and the six classes divided the 13599 images. Among these, 3 are rotten fruits, and the other 3 are fresh fruits. This RetinaNet model tests the mean average precision with a higher cost.

Nosseir et al. [30] to automatically differentiate between rotten and fresh fruit, a Support Vector Machine (SVM) and a K-nearest neighbors (KNN) combination was developed. The picture of the fruit's texture and colors are extracted using a matrix called GLCM, which stands for grey-level co-occurrence matrix. SVM separates the segmentation and linear values to determine which fruits have deteriorated and which are still fresh. This helps to tell the difference between rotten fruits and fresh fruits. Accuracy levels of 98% and 96%, respectively, were achieved using the quadratic and linear SVM.

Hossain et al. [31] For industrial applications, deep learning (DL) for automatic fruit classification. Six CNN light models and the pre-trained deep learning model fine-tuned the CNN model. This model outperformed a better and more efficient framework, 99.49% accuracy Better and efficient framework and 99.49% accuracy with higher cost and time complexities.

Abu-Saqer et al. [32] suggested deep learning to classify the type of grapefruit. The fruit had long been regarded as a valuable vitamin source and a preventative measure for deficiencies of vitamins A and C. Individuals who consume fruit as part of a nutritious diet are less likely to develop long-term illnesses. The Python software-based white and pink grapefruit types were recognized. The deep learning model achieved an accurate and automatic detection model with poor scalability outcomes.

Saranya et al. [33] introduced deep learning-based CNN over SVM and KNN to classify fruits. Various kinds of fruits like pomegranates, oranges, bananas, and apples were classified concerning the fruit-360 dataset. This model demonstrated a suitable and better feature extraction model with more time consumption.

El-Kahlout et al. [34] presented the deep neural network model to classify fresh and defective peaches. Vitamin A levels are exceptionally high in golden varieties. Peach trees have a limited lifetime compared to certain other orchards. Utilized a supervised neural method for image recognition in which 30% for validation and 70% of the image for training based on a total of 2,306 images. This model delivered better feasibility and higher cost.

Mettleq et al. [35] introduced convolutional neural networks for the classification of mango. Various features from the mango, like flesh color, skin color, sweetness, shape, and size, are extracted. Two categories set of data of 1200 image data is provided for the classification of the mango method. CNN algorithms were employed, a supervised neural technique widely used in machine vision. These findings were revealed because when Convolution neural Mango categorization apps are used in automated categorization processes, individuals can correctly recognize the kind of mango. The qualified approach achieves a considerable percentage of accuracy in the testing set, proving its viability. This approach delivered higher reliability and training accuracy but was unsuitable for large datasets.

Alajrami et al. [36] introduced deep learning-based CNN to classify the types of tomatoes. Tomatoes are a good source of Vitamin C and salts and thus are suggested for people suffering from incontinence, kidney disease, and cardiac and body illnesses. Research findings and research data have shown that eating tomato juice reduces red blood cell action in diabetes patients, which protects people from creating fatal clots. This model demonstrated 93% testing accuracy and faster prediction and failed to extract the features.

Ukwuoma et al. [37] introduced deep learning techniques to detect and classify the fruit’s quality. Easy to see and rank the fruits. Contains the findings of various deep-learning methods used in previous research for fruit classification and detection. To help novice agricultural investigators understand the role of deep learning in agriculture, they built a deep-learning model for citrus categorization from the sketch using the famous dataset "Fruit 360." It demonstrated possible detection results with higher computational time during classification.

Elwirehardja et al. [38] suggested deep learning-based EfficientNetB0 approaches to classify the ripeness of oil palm fresh fruit bunches. ImageNet transfer learning was applied to four lighter weight Convolutional networks using a novel data augmentation method called "9-angle crop," which was then optimized using post-training classification. This model outperformed higher accuracy, precision, and recall percentages with minimum time consumption and more complex computational resources.

Shahi et al. [39] introduced attention-based MobileNetV2 to classify fruits' freshness. The suggested technique, which employs a transfer learning approach, outperforms the same four most recent deep-learning algorithms with fewer groups of learnable parameters and outstanding classification accuracy when tested on three major berry data sets. This model demonstrated better classification accuracy with many trainable parameters and is unsuitable for automatic detection due to huge dimensionality features. Food safety has become a world concern with the reduction of food production worldwide due to the encroachment of agricultural lands for industrial purposes. So, it is necessary to classify the fruits as fresh and rotten to dispose of the waste fruits for other valuable purposes and protect the fresh fruits from getting rotten.

Jana et al. [40] presented a novel approach to classify fruits based on convolutional Neural Networks (CNN). The authors use four Convolution layers to separate the features from the images taken. The classification accuracy obtained is equal to almost 99.87%, and it provides stable outcomes irrespective of the fruits and vegetables. However, it failed to detect the level of freshness to separate or use as soon as possible.

Pathak et al. [41] demonstrated a novel CNN-based Transfer Learning approach for classifying fruits such as apples, bananas, and oranges as rotten and fresh. The features were extracted with the CNN, and new and rotten fruits were segregated with a softmax layer. The authors stated that the classification accuracy of 98.13% is achieved and exclusively applicable for those selected fruits and failed to classify the other types of fruits and vegetables.

Garillos-Manliguez et al. [42] presented the maturity of the fruits, especially papaya fruit, which is analyzed by utilizing a non-destructive and multimodal classification approach. The authors explicitly use the deep CNN for the estimation of the maturity of the papaya with the features acquired from two imaging models such as (i) Visible light and hyperspectral imaging. For the sensitivity analyses, the authors changed architectures such as MobileNetV2, ResNet150, VGG19, AlexNet, VGG16, and ResNex150. The F1 score is about 90%, with a 2% error rate during the classification. However, using deep learning approaches might cause overfitting issues due to the variable figure sizes and petite sizes; however, increasing the figure size adversely affects the memory size.

Ganguli et al. [43] stated a novel approach known as the CNN-based MLP approach. Classification of fruit maturity using a machine learning algorithm is an intricate process. The type of fruit ripeness impacts the agriculture quality and delivery process to shops. The presented system detects the maturity of bananas with their sizes. The data are collected using CNN and MLP and classify the bananas with an accuracy of 99%. Here the authors utilize the imaging of RGB and hyperspectral imaging combination. Meanwhile, this approach is affected by potential overfitting issues and applies exclusively to the classification of the maturity of bananas.

MacEachern et al. [44] delineated an approach for classifying the ripening of wild blueberries and estimating yields. The authors stated the process with six models such as YOLOv4, YOLOv4-Small, YOLOv4-Tiny, YOLOv3, YOLOv3-SPP, and YOLOv3-Tiny. The authors classified the three types of berries, red, blue, and green, with two classes, ripe and unripe. Meanwhile, YOLOv4 achieves a better performance of mean average precisions of 88.12% with little computational overhead.

Hassanzadeh et al. [45] presented a novel imaging spectroscopy-based unmanned aerial system (UAS) to predict the snap bean. Evaluating crop maturity at a time is essential to avert the loss of food, fruits, and vegetables. Most of the work carried out is time-consuming and expensive and hence. The UAS-based hyperspectral utilizes visible-to-near infrared region. The features were extracted using the library Jostar incorporated with ant colony optimization and simulated annealing to predict the five spectral features. The classification was carried out with the support of the decision and random forest classifiers. The F1-score concerning the type of bean as ready to harvest and not willing to gather is 91%. However, this is exclusively used for the classification of snap beans.

Sharma et al. [46] to automatically differentiate between rotten and fresh fruit, a Support Vector Machine (SVM) and a K-nearest neighbors (KNN) combination were developed. The picture of the fruit's texture and colors are extracted using a matrix called GLCM, which stands for grey-level co-occurrence matrix. SVM separates the segmentation and linear values to determine which fruits have degraded and which are still fresh. This helps to tell the difference between rotten fruits and fresh fruits. Accuracy levels of 98% and 96%, respectively, were achieved using the quadratic and linear SVM.

Shah et al. [47] a revolutionary handheld fruit ripeness meter that does not cause damage and is non-destructive. It does this by explicitly predicting the maturity state of the mangoes as either ripe or immature using the KNN to anticipate when it will be possible to pick mangoes that are still on the tree. When the writers of this work compared it to other studies that use an indirect maturity index, they found that it had an accuracy of 88.3%, whereas the indirect maturity reveals that it only has an accuracy of 55.8%. The results of this experiment are only utilized to categorize adult mangoes and a limited dataset.

Ashtiani et al. [48] referred to an innovative computer application that is based on computer vision known as CNN. To forecast when mulberries will be ready to pick. In CNN, the process of transfer learning-based tuning is carried out to reduce the amount of money spent on training and to improve classification accuracy. When it comes to correctly categorizing white and black mulberries, the CNN models AlexNet and ResNet-18 can get superior results of 98.34% and 98.66%, respectively. The accuracy is not contingent on the number of photographs that are utilized, and results are provided without regard to the data. 2.36 minutes is the amount of time that was used for the categorization. But, to protect the fruits from being harmed, it is important to divide them into four categories.

Zhou et al. [49] stated an automatic strawberry maturity classification with the YOLOv3 technique. Predicting the ripeness as matured and immature to improve the strawberry yield is necessary. This is widely used for detecting small objects and is trained to expect the flowers of strawberries and fruits with different maturity levels. For the uncrewed aerial vehicle (UAV) images, the highest mean average precision (mAP) is 88%, and the highest classification average precision (AP) is 93%. However, the computational complexity is higher due to the classification of the seven stages of strawberries.

Lawal et al. [50] demonstrated a novel YOLO Muskmelon approach for the prediction of fruits in a fast manner and to surmount difficulties. The stated policy is combined with a ReLU-activated ResNet43 backbone that has a new 2, 3,4,3,2 residual block arrangement, spatial pyramid pooling (SPP), complete Intersection over Union (CIoU) loss, feature pyramid network (FPN), and distance Intersection over Union Non-Maximum Suppression. This is done to improve the detection performance. In addition to having a detection speed of 96.3 frames per second, the average precision (AP) is also 90%. On the other hand, it is essential to enhance the accuracy of the categorization.

Wang et al. [51] Fruits' external appearance is one of the most critical factors in customers' decisions to purchase or reject them; hence packing facilities need to implement systems that can identify fruit skin flaws before the fruits are packed into batches and sent to the final consumers. This research suggests a new approach to detecting fruit skin flaws using a Visual system. This approach is more accurate and needs less computational effort. The color histogram is extracted as an image feature in the local picture patch, and the Linear SVM is utilized for training the model. Out of 650, 300 photos were used to prepare the SVM model to correspond to the poor skin scenario. Another 50 unfavorable skin pictures with 61 abnormalities are sent for analysis. In this work, the SVM color classifier does not pick up the remaining two problems since they are not as visible as the other 59 defects. Recall percentage: 59/61 = 96.7%. It would be problematic if producers failed to discriminate between various sorts of problems when seeing external flaws in fresh fruits. It is crucial that the appearance of leaves, dirt, or any other foreign matter be distinguished from actual skin flaws. Future studies should focus on a more intricate approach that considers both speed and accuracy when categorizing fruits according to the exterior spots they exhibit. Producers can distinguish between rotting or severely damaged and must reject other fruits with minor flaws that merely impact their look and can be sold as second-quality. They created a novel approach to check fruit layer flaws that is greater precise and requires less computation. This technology can be used by packing plants to separate good ones from damaged fruits before wrapping them in batches, guaranteeing the quality of the goods at this point.

Kawano et al. [52] work achieved a classification accuracy that was substantially higher than the best result that has been previously published for this dataset, which was 59.6%. The combination of these three features yielded the most significant performance for the UEC-FOOD100 dataset. This resulted in an increase of 72.26% in the top-1 accuracy and 92.00% in the top-5 accuracy, which was an improvement over the previous high of 59.5%. This demonstrates that the suggested system has properties that are distinct from those of traditional local features and Fisher Vectors. Moreover, it demonstrates that combining these systems rather than relying on a single one is the key to enhancing performance. This is a very positive result for the real implementation of the technology behind food photo recognition. For food picture identification, the authors of this study proposed merging pre-trained DCNN features taken from the ILSVRC 1000-class dataset with DCNN features. They were able to categorize the UEC-FOOD100 dataset with the highest accuracy, which demonstrates that integrating DCNN components with conventional features may increase classification performance. The experimental findings can be seen here. They have decided that, for their future development, their primary focus would be on implementing the features on mobile devices.

Kagaya et al. [53] suggested a convolutional neural network to detect and identify food-related visual challenges. Given the incredible variety of food varieties, recognizing images of food products is typically exceedingly challenging. CNN is a cutting-edge deep learning method; however, new research has revealed deep learning to be a compelling image identification technology. Through parameter optimization, they used neural networks to perform the critical task of detecting and recognizing the food. CNN achieved a level of accuracy that was far greater than that of earlier support-vector machine-based techniques that used handcrafted features. In addition to this, they found that color is the most important factor in the process of feature extraction, as evidenced by the convolution kernels. CNN also demonstrated noticeably greater accuracy in recognizing food images than a traditional approach. The assessment of food item recognition requires many photographs of typical meals. Usually, a dinner image includes a variety of foods. Each food item location in the image must be recognized and isolated for the dataset to evaluate food item recognition. For this reason, food-tracking apps for cell phones can offer some excellent data; they used Food Log's data. Generally, they use FL to record their meals using text and photographs. By entering the food item’s name on the smartphone’s display, the user takes a photo of a meal and identifies each region containing a food item. The food item’s name is often selected from a typical food database. This results in producing immaculate data regarding image regions of specified food products. Because users typically prefer small areas for the food items, the domains that users defined in our studies with food recognition were somewhat increased. FL is a freely accessible app, and as more people use it, the food item dataset is also growing. The usefulness of CNNs for food image recognition and detection has been discussed in this work. First, they created a food image dataset using pictures numerous authentic people provided. Second, they tested CNN's performance in recognizing ten different food items. They discovered that CNN outperformed conventional techniques that used handmade characteristics significantly. Third, they observed trained convolution kernels and demonstrated that color features are crucial for food image recognition. Fourth, they used CNN to detect food and discovered it performed noticeably better than a baseline approach.

Singla et al. [54] The image-based dietary assessment subject has recently undergone many advancements. The classification and recognition of food images are essential in evaluating a diet. Two of the photo datasets that were created initially were utilized for these investigations. The photographs originated from a variety of sources, including imaging databases that were already in existence, social media platforms, and other imaging equipment, such as cell phones and wearable cameras. The categorization of food as either food or not food, or the determination of whether or not an image contains food, is an example of a binary classification issue. A food classifier analyses a picture and decides whether or not the image depicts food based on its features. In the same way that other image classification problems can be solved using machine learning techniques, this can be solved by training a classifier using picture data. The GoogLeNet model, which was recently developed based on a deep neural network, is utilized in this investigation to differentiate between food and non-food photographs, after which the food photographs are assigned to one of 11 categories. The efficient and successful deep neural network design that is known as GoogleNet includes a level of organization that is referred to as the "Inception Module." There are nine of these types of modules included in the architecture of GoogleNet, and the processes that make up each one include convolutions and max-pooling. To facilitate training, validation, and assessment, the two datasets have been segmented into three subsets respectively. The main factors that contribute to the low identification accuracy of some food photographs include the intricate mix of food components that are depicted in the image, as well as the remarkable visual similarities that exist between some photos from other categories. They use a multi-label technique to identify food items in pictures and compare them to other architectures like AlexNet, VGG, and ResNet.

Ragusa et al. [55] presented A significant research challenge in developing a mechanical comprehension of food. This software can help track a patient's eating habits and diet from photographs taken with wearable or mobile cameras. The ability to distinguish between photos containing food and other images is one of the initial difficulties in the sector. Existing categorization methods for quality and non-quality food have combined deep representations of different classification techniques. However, they have typically been assessed using various procedures and data, making an accurate comparison of the performances of the currently available methods impractical. This study compares a publicly available dataset to the most recent classification methods used to classify foods against non-foods. Having a True Positive Rate of 94.28% and a True Negative Rate of 95.50%, performances are balanced between the new and damaged food classes, giving a total accuracy of

94.86%. It should be noticed that this combination performs significantly better than the softmax classifier used in the fine-tuned network. This mismatch is likely caused by the fact that training a binary SVM model is a finite process that only improves the classifier component. However, teaching a CNN is probabilistic and simultaneously enhances both the representation and the classifier. The distinction between food and non-food has been explored utilizing shallow and deep drawing and other categorization techniques. They have discussed this study's most popular classification approaches to create a reliable and effective classifier that distinguishes food and non-food. Such methods are often evaluated on non-public data using various methodologies. According to the results, a binary SVM classifier with a fine-tuned AlexNet model produces the best outcomes. Future research will optimize the suggested approach to use less memory and processing power. Additionally, this model will be considered the foundation for a wearable camera application for food logging.

Azizah et al. [56] developed One fruit with significant export potential in Indonesia mangosteen. But not all mangosteen fruit is free of flaws. Mangosteen export quality control is carried out manually by a sorting specialist. As a result, this can produce unreliable and erroneous findings. Human error is the cause of the outcome. To aid in the process of separating the defects from the non-defects, image processing technology is required. Convolutional neural networks are one deep learning architecture they use in this study. As a result, they employ CCN to identify mangosteen. Regarding picture classification, CNN has proven to be quite effective. To verify the accuracy of the data used in this CNN approach, a 4-fold Validation Cross is used. The mangosteen fruit itself has been manually categorized and sampled. The photos are organized based on the data needed for the investigation. One image from the data retrieval shows two mangosteens. Before the picture is processed using the Neural Networks classification algorithm, this stage aims to create homogenous image data input. However, the distance at which the image was taken and the size of the natural mangosteen could impact the outcome. As a result, the image needs to be cropped and resized. The idea is cropped and resized to 512x512 pixels. Resize would thereby speed up CNN processing. This study uses 120 test photos—30 images with defects and 90 without—split into four separate data sets for deep learning classification utilizing the CNN algorithm and four-fold cross-validation as image classifiers. A detecting program is created to test each of the folds. The folds produce an overall accuracy percentage that can be used as a success rate indicator. Our suggested technique can detect the mangosteen fault surface with a superior accuracy of 97.5%. Even though the system has an incorrect reading, it is typically less than 2.5%.

Sonali et al. [57] the author suggested a waste management system for a society with cutting-edge features like automatic lid opening and closing when someone approaches the trash can and the detection of toxic gas. Separation of home garbage into biodegradable and non-biodegradable categories on two levels: creating compost from the biodegradable waste and notification of the municipal corporation and the society's manager via Google Messenger. The suggested smart trash can distinguish between biodegradable and non-biodegradable waste and separate it into two compartments. The proposed model is beneficial for preserving society's health, cleanliness, and ecology through machine learning. At K = 3, 4, and 6, the KNN model's total accuracy is 93.3%. The fabricated bio composts made from trash at the societal level can be utilized to maintain society's greenery and make money by selling the compost. The municipal corporation can also deal with or collect the separated non-biodegradable garbage. The suggested structure effectively benefits society through garbage collection, separating biodegradable and non-biodegradable household waste, and composting waste. The proposed model is beneficial for preserving society's health, cleanliness, and ecology through machine learning. At K = 3, 4, and 6, the KNN model's total accuracy is 93.3%. The fabricated bio composts made from trash at the societal level can be utilized to maintain society's greenery and make money by selling the compost.

Raheel et al. [58] used the Fruits 360 dataset. Each fruit variety has a somewhat different number of images in the training and test sets. In most cases, roughly 90 percent of training images and 10 percent of test pictures for each fruit category. 100 by 100 pixels are used in each image. Using a 14-layer neural network that was self-designed, the classification problem for fruit photos was addressed. To train the network, enhanced data is used. The creation and training of this CNN didn't use any pre-trained models. This tells the performance of situations involving transfer learning and fine-tuning. Using the VGG16 model, transfer learning is accomplished. Furthermore, fine-tuning and transfer learning significantly improve categorization accuracy. The classification accuracy shows the proportion of the test set's 12,132 images correctly classified.

Shawon et al. [59] suggested a system that can identify fresh or rotten fruit from an input image after being trained on a dataset of fruit images. In the area of image recognition and classification, the model that has seen the greatest amount of adoption is the convolutional neural network. Human inspection is the method that is utilized by the vast majority of supermarkets and fruit vendors when determining the overall quality of the fruits that are stocked in their establishments. On the other hand, this process may be automated. They developed the initial model with the help of the Inception V3 model, which was subsequently trained with the help of our dataset through the use of transfer learning. Our dataset comprises 1734 photos. The photographs were obtained by downloading them from various web search results as well as local fruit shops. At first, they compiled a data collection consisting of 353 photographs taken from Google Image Search. These photographs depicted both fresh and decaying examples of bananas and mangoes. After that, they included pictures of oranges and apples, both of which were in their fresh and decayed states. Also, they added some images to the categories that already had images.

The new collection was gathered mainly from neighborhood fruit markets and then condensed into a more manageable dataset. One thousand three hundred eighty-one more photos were added to the group during this round of dataset construction. During this phase of dataset construction, 1381 more images were added to the collection. The main issue ran into during image collection was the absence of datasets of a similar nature, as well as the fact that no prior attempt had been made to categorize fruits solely based on whether they were fresh or rotten. Not all fruits grow the same way in every region of the world is a drawback of collecting photographs from the internet. Finding an image of a local fruit-grown variation of a particular fruit is occasionally very difficult, especially if people have yet to write anything about it on the internet. Their shape also changes depending on the weather, soil, and other circumstances. The challenge with gathering photos from neighborhood fruit stands is that not all vendors will allow customers to take snapshots of their produce. The automation of quality evaluation procedures for determining whether fruits are fresh or rotten is promising. Many superstores can decrease costs connected with manual quality assessment inspection and prevent human error with the help of this automated solution. In this study, they developed a model to categorize apples as fresh or decaying using a label and a likelihood score. They developed our strategy on CNN. They used the Inception v3 model for multiclass classification and the VGGNet16 model for binary type. They achieved excellent results for binary classification;

Nasiri et al. [60] The approach for distinguishing healthy date fruit from faulty ones is new and accurate according to this study. The use of deep CNN also allows this technology to forecast the stage of ripening for fresh dates. The Visual Geometry Group -16 architecture was utilized to build the suggested Neural Network model, followed by different layers. This dataset was gathered using mobile in unconstrained lighting and camera parameter settings, including stabilization and focus. The overall classification accuracy for the CNN model was 96.98%. Shahani dates, regarded as damp date fruits, were chosen for this investigation. In Jahrom, one of southern Iran's most significant areas for horticulture products, the best variety of Shahani dates is frequently grown. Images of each sample were taken using the LG-V20 smartphone camera. Each picture has a consistent background.

Other factors need to be fixed, such as focus, the angle at which the photograph was taken, the lighting, and the distance between the camera and the samples. Over 1300 photos of both good and unhealthy dates were included in the collected dataset. There were 327, 288, 284, and 458 photos in each of these classifications. Deep Convolutional Neural Networks (DCNN) have an excessive number of parameters. To learn all the parameters, the training phase needs a sizable dataset of training images; Since it is frequently impossible to develop the number of input photos without increasing costs and processing time, data augmentation must be used. The training dataset is extended with the same label or class in the data augmentation approach to avoid the over-fitting problem. The updated CNN model was trained on the training dataset five times using 25 epochs each time.

Jiang et al. [61] In this paper, they suggest a technique for quickly identifying diseases in apple fruit and preventing future infections brought on by environmental factors. Images of apples are classified using deep learning, which has proven to be effective in image processing and classification. They assess and rate deep neural networks with various convolutional layers and numbers of neurons. Additionally, a comparison with the research on apple picture classification that was previously reported has been made, and the superiority of the suggested method is demonstrated. The proposed technique to find the apple fruit's color shift will be noted. They'll show how using CNN for deep learning and image processing can beat the SVM method's accuracy. Several CNNs with various layer configurations will be investigated and assessed in this manner. The output of the last layer decides whether the disease is present or absent in photos of apples and fruits. The network that exhibits greater accuracy is the ideal and conclusive structure. These factors together account for this performance.

On the other hand, when image size reduces, the number of parameters in the network also lowers, speeding up and simplifying the network training process. The image set used in this work consists of 3279 thousand fruit-related grey images. The photos' 460x560 dimensions will increase the computing load throughout the training and evaluation phases. To speed up processing and promote network convergence, the measurements have been decreased to 215x280. By receiving fruit photos, the network eventually labels the visuals as healthy or unhealthy in its output. The apple fruit disease picture dataset was downloaded from ULG Belgium and used for research in this paper. The dataset includes multispectral images of infected and healthy apples at wavelengths 450, 500, 750, and 800 nm.

The bi-color photos are manually segmented for the diseased areas. An expert then examined the apple's properties. Rot, flesh damage, bruises, forest damage, russet, and other faults come in different varieties. Still, for the sake of this research, they classified the photographs into two groups: healthy and diseased. For quicker processing, resized the photos to 215x280. IoT environments have the potential to be more innovative, especially in the agriculture sector. In this study, they suggested a convolution neural network-based technique for identifying diseased apples. The grey apple image set is used to train a deep neural network. The convolution neural network retrieved the key elements used for critical categorization from Apple photos. There are two categories for apple images: infected and non-infected. The construction of a neural network includes two fully linked layers and three convolutional layers. Although the accuracy of picture categorization has increased thanks to deep learning, the learning process is time-consuming. Additionally, a sizable dataset is needed for network training.

Mureşan et al. [62] presented a fresh, high-quality collection of pictures of fruits. They also discuss some numerical experiments conducted to train a neural network to recognize fruits. They examine the rationale behind our decision to employ fruits in this project by putting forth a few applications that could use such a classifier. They outline the data set's composition and methodology in this section. The photos were created by recording the fruits as a motor rotated them and then separating the individual frames. A low-speed motor's shaft was lined with fruits, and a 20-second movie of the event was captured. They used a white piece of paper as the background behind the fruits. They created a unique algorithm to extract the fruit from the backdrop because the experience was not uniform due to fluctuations in the lighting conditions.

This approach is of the flood fill type: starting at each image's edge, they mark all pixels. Next, they keep any more pixels discovered nearby that have colors closer together than a predetermined threshold. They repeat the preceding procedure until no more pixels are left to mark. Fruits were resized to suit an image with 100x100 pixels. Other datasets employ 28x28 prints. However, they believe that a tiny size is problematic when there are too many comparable items. They intend to work with much larger photos in the future, but this will necessitate considerably longer training periods. They employed a convolutional neural network for this project. Valid padding is comparable to having none. On the one hand, pooling layers are utilized to scale down the network's processing and the representation's spatial dimensions.

Pooling layers are also used to prevent overfitting. The most common pooling layer filters are 2 x 2 with a stride of 2. The input is practically cut in half as a result of this. A typical neural network has layers that are fully coupled. Each output from a fully connected layer is associated with each neuron from that layer. Convolutional layers use the same procedures as fully connected layers. Consequently, conversion between the two is conceivable. They can build queues using these files so that the data may be fed to the neural network. They preprocessed each image in the batch to expand the data set. The preprocessing entails applying random vertical and horizontal flips and changing the hue and saturation at random. They employ the unexpected hue and random saturation TensorFlow algorithms for hue and saturation. Each image from the batch was converted to grayscale and concatenated to the image to increase the network's accuracy further. As a result, the network will receive data that is 100 by 100 by 4 in size. They preprocessed each image in the batch to expand the data set. The preprocessing entails applying random vertical and horizontal flips and changing the hue and saturation at random. They employ the unexpected hue and random saturation TensorFlow algorithms for hue and saturation.

Each image from the batch was converted to grayscale and concatenated to the image to increase the network's accuracy further. As a result, the network will receive data that is 100 by 100 by 4 in size. Using cross-validation, they determined the accuracy of every 50 steps. This demonstrated the network's gradual improvement up to its 100% cross-validation accuracy. They used the testing set for the testing phase and computed an accuracy of 96.3%. From our perspective, increasing the neural network's accuracy is one of the primary future goals. This entails experimenting more with the network's structure. Different adjustments and modifications to existing layers, as well as the addition of additional layers, might provide entirely different outcomes. Another choice is to swap out every layer for a convolutional layer. It has been demonstrated that this offers some advantages over networks with completely connected layers. They intend to develop a mobile application that will soon snap images of fruits and label them appropriately.

Table 2.1: Literature analysis based on study and analysis of food waste management

Author	Year	Method used	Advantages	Limitations
Jahanbakhshi et al. [23]	2020	Deep Convolutional Neural Networks (DCNN)	Better accuracy with efficient management of waste	Need to extract the characteristics of quality and geometric agricultural products.
Ünal et al. [24]	2020	Convolutional neural network	Increased number of training datasets and good recognition	Higher cost and complexity
Altaheri et al. [25]	2019	CNN-based ALEXNET architecture	Higher accuracy rates with minimum execution time	Higher feature dimensionality
Bhargava et al. [26]	2020	Artificial neural network, K-nearest neighbor, Sparse representation classifier, and Support Vector Machine (SVM)	Maximum accuracy and better-quality evaluation outcomes	A large number of fruit images affects the overall system performances
Ashraf et al. [27]	2019	CNN	Minimum cost, low dimensionality, and a better probability Score	Difficulties in feature extraction steps

Singla et al. [28]	2018	Pre-decided grading criterion	Enhanced speed of fruit quality selection	More significant computational difficulties and complex time execution
Perez-Daniel et al. [29]	2020	One-stage object detector-based RetinaNet model	Highest accuracy and better mean average precision	Higher cost and minimum reliability
Nosseir et al. [30]	2019	SVM and KNN	Good detection accuracy	More feature dimensionality to reduce the overall performances
Hossain et al. [31]	2018	Deep learning (DL)	Better and efficient framework with 99.49% accuracy	Higher cost and time complexities
Abu-Saqer et al. [32]	2020	Deep learning	Accurate and automatic detection model	Poor scalability
Saranya et al. [33]	2020	Deep learning-based CNN with SVM and KNN	Suitable and better feature extraction model	More time consumption
El-Kahlout et al. [34]	2020	Deep neural network model	Better feasibility	Higher computational cost

Mettleq et al. [35]	2020	Convolutional neural networks	Higher reliability and higher training accuracy	Not suitable for large dataset
Alajrami et al. [36]	2020	Deep learning based on CNN	93% testing accuracy and faster prediction	Failed to extract the features
Ukwuoma et al. [37]	2022	Deep learning techniques	Feasible detection results	Higher computational time
Elwirehardja et al. [38]	2021	Deep learning based EfficientNetB0	Higher accuracy, precision, and recall percentages with minimum time consumption	High complex and computational resources
Shahi et al. [39]	2022	Attention-based MobileNetV2	Better classification accuracy with a small number of trainable parameters	Not suitable for automatic detection due to huge dimensionality features
Jana et al. [40]]	2021	Convolutional neural Networks (CNN)	Classification accuracy is 99.87% and is stable for all fruits and vegetables.	It failed to detect the level of freshness.
Pathak et al. [41]	2021	CNN based Transfer Learning approaches	A classification accuracy of 98.13% is achieved	Failed to classify the fruits other than apple, Banana, and orange

Manliguez et al. [42]	2021	Non-destructive and multimodal classification and CNN	The F1 score achieved is about 90%, with the 2% error rate	Overfitting issues due to the variable figure size petite sizes; however, increasing the figure size adversely affects the memory size
Ganguli et al. [43]	2022	CNN and MLP, RGB, and hyperspectral imaging combination	Classification accuracy is 99%	Potential overfitting issues and applicable only to bananas
MacEachern et al. [44]	2022	YOLOv4, YOLOv4-Small, YOLOv4-Tiny, YOLOv3, YOLOv3-SPP, and YOLOv3-Tiny	The mean average precisions obtained is 88.12%	Little computational overhead
Hassanzadeh et al. [45]	2021	Imaging spectroscopy-based unmanned aerial systems (UASs), decision trees, and random forest classifiers	Higher F1 score of 91%	Exclusively used for the classification of snap beans, and that is the limitation.
Sharma et al. [46]	2022	Partial least squares regression (PLSR) and k-nearest Neighbors, genetic	The test accuracy achieved was 93.7%, RMSEP<1.6%	Computational overhead

		algorithm, and principal component analysis (PCA)		
Shah et al. [47]	2021	Non-destructive hand-held fruit maturity meter, KNN	Accuracy is 88.3%	They are exclusively used for small-scale datasets and the maturity of mango detection.
Ashtiani et al. [48]	2021	Transfer Learning based CNN, AlexNet and ResNet-18	Achieves better accuracy of 98.66% within a time of 2.32 mins	However, to avoid damage to fruits, it is necessary to classify the fruits into four classes
Zhou et al. [49]	2021	YOLOv3 technique, uncrewed aerial vehicle (UAV) images	The highest mean average precision (mAP) is 88%, and the highest classification average precision (AP) is 93%	The computational complexity is higher due to the classification of the seven stages of strawberries
Lawal et al. [50]	2021	YOLO Muskmelon, SPP, FPN, and distance Intersection over Union−Non-Maximum Suppression (DIoU−NMS)	The average precision (AP) is 90%, with a detection speed of 96.3 frames per second.	Detection accuracy is lower.
Wang et al.	2013	Linear Support	The accuracy is 96.7%	Improve the Model

[51]		Vector Machine (SVM)		for better accuracy and to engage more categories.
Kawano et al. [52]	2014	DCCN	The accuracy is 92%	Improve the model to work on mobile devices.
Kagaya et al. [53]	2014	CNN	F1 score of 93%	Detection accuracy is lower.
Singla et al. [54]	2016	GoogLeNet	Low accuracy was detected at about 92%	Improve the accuracy
Ragusa et al. [55]	2016	Fine Tuned AlexaNet	94.68% accuracy recorded.	We need to classify some fruits.
Azizah et al. [56]	2017	CNN	Test Accuracy 97.5%	Increase the number of fruit categories to build a sophisticated model.
Sonali et al. [57]	2020	KNN Classifier	The Accuracy is 93.3%	An additional focus is required in separating biodegradable and non-biodegradable.
Raheel et al. [58]	2019	Fine Tuned and Transfer Learning VGG16	Performance-wise is good.	Improve the Model accuracy to the expected.
Shawon et al. [59]	2019	Fine-tuned Inceptionv3 and VGG16	Multiclassification was done and showed good performance.	Increase the number of fruit categories.

Nasiri et al. [60]	2019	Deep Convolution Neural Network	The classification accuracy is 96.98%	Work also should carry on vegetables in addition to fruit categories.
Jiang et al. [61]	2021	CNN	Detects accurately and classifies the categories.	Focus on infected and non-infected.
Mureşan et al. [62]	2018	Convolution Neural Network	The accuracy recorded as 96.3%	Focus on Mobile Applications.

2.1 Research Gaps in Food Waste Management

In the area of food waste management, in the literature, we have observed that some problems need to be addressed properly. The researchers who are working on food waste are exploring the problems to solve and provide the solution. The following are some problems identified from the current literature. These statements can give some insights to the upcoming researchers to start their work. We have also formulated the problem statement [2.3] with the help of literature.

- Improving food tackling the methods for measuring food waste [43].
- Improving the detection of food waste items [45][47].
- Improve the accuracy of detecting fruit classification [44][29][53].
- To solve the problem of overfitting in classifying the fruits [42][61].
- To reduce the computational time in building and evaluating the model [31].
- To work on large data sets to predict correct accuracy [26].
- Improve the model to work for larger datasets [39].

2.2 Motivation

According to reports from the United Nations Environment, there is a waste of 130 crore tonnes of food. Shops, restaurants, and homes all produce significant food waste. Since there are no practical ways to deal with the wastage of food at distinct levels, including families, restaurants, and food supply chains, the number of recipes in the world is rapidly decreasing. Cooking too much and additional elements are to blame for a large bulk of food wastage in both homes and restaurants. They need to be able to differentiate between fresh food and food that has been damaged to reduce the amount of food that is wasted. If the defects are not identified, a diseased apple may spread the illness to a healthy apple. It is more probable that food will be wasted, which can cause a variety of problems. To achieve the Sustainable Development Goal (SDG) 12.3 objective, there must be a reduction in food waste at the consumer and retail level, as well as a reduction in losses in the supply chain. On the other hand, the population is growing at an alarming rate, yet we cannot store all of the necessary food products to combat malnutrition and other illnesses that are closely associated with it.

From our current literature, we have learned that the majority of the food is wasted in households and the rest of the wastage comes from other factors like retail, shopping, exporting and importing, overcooking, plate waste, buying, etc. If we observe the wastage of food from the household, it is because of the lack of a refrigerator, unplanned shopping, and the expiry of the stored items. We can also understand from the literature on some restaurants, that food wastage is heavy due to not eating properly and throwing in the dustbins due to different factors by the customers. In the case of packaging the food items to deliver to the customer, because of the improper package also some food is wasted. While transporting the items from one place to another place there will be unexpected wastage.

As we all know, many outlets are offering food items in their stores. Due to the expiry of those items also more wastage is comes. To solve this issue, some markets are providing many offers to clear the food items that are expiry shortly. But these all may need human intervention to save every time and there should be regular monitoring by the workers in their outlets. Some food items are very sensitive in nature in the case of damage like if we take fruits, vegetables, etc. In major cities, we have many rythu bazaars conducted on weekdays depending on the area for some period in the day. Once that period is over, these all vegetables and fruits are spoiling due to different factors like temperature, pollution, exposure to the sun, and other reasons. In supermarkets, these sensitive food items like vegetables, and fruits will be arranged with some care not to spoil immediately. But, after some time damaged items will be thrown into the dustbins. These all happen because of not taking proper measures on food items to safeguard and use them carefully. In turn, from all the directions, we can easily understand there are some problems in identifying the fresh food items and those that are damaged. So, if we try to solve this issue there will be progress in protecting against food wastage and feeding more people in the country.

2.3 Problem Statement

The problem statement is prepared from the study of literature and after identifying the research gaps. They have focused here mainly on the reduction of food waste by applying different techniques using deep learning. This study concentrated on identifying the three fruit varieties, apples, oranges, and bananas, in their fresh and damaged stages. Since fruits have a wide range of shapes, colors, sizes, textures, and other features, classifying them can be challenging. There are many applications for a reliable and durable solution to this problem. One practical and urgent use of such a system is determining supermarket prices. Cashiers at supermarket checkout counters conduct a critical task called fruit classification. These cashiers must be able to recognize both the kind and variety of fruit to determine prices.

2.4 Objectives of the Study:

1. To study and analyze the various existing food waste management techniques.
2. To propose a new technique for food waste management using deep learning techniques.
3. To design an ensemble approach for accurate measurement of the designed technique.
4. To compare and analyze the proposed work with the existing approaches.

2.5 SUMMARY:

This chapter explains and reviews the existing methodologies for classifying fresh and rotten fruits and waste management. This section discusses the methods, platform for implementation, benefits, and limitations of current works. Also, learners may see how various approaches implemented forward by other researchers are put into practice. Most of the work was carried out using a powerful mechanism to detect and classify the images called Convolutional Neural Network. This technology has been thoroughly discussed in Chapter 1. The rules of previous studies are evaluated and improved in the proposed work using a novel deep-learning model based on this investigation.

Chapter 3

Novel CNN Model to detect and classify Fresh and Damaged Fruit

This chapter covers the proposed technique to detect and classify fresh and rotten fruit to reduce the wastage of food. The proposed model Novel Convolutional Neural Network (CNN) developed from scratch for classifying images. The data set was considered from the Kaggle website and also applied some preprocessing techniques to make it clear for recognition and classification [Section 3.4]. The performance evaluation has been done based on parameters like classification accuracy, Precision, Recall, and F-Score. Finally, the model is compared with some existing systems to show the performance of the model.

3.1 CNN Basic Architecture:

The convolutional neural network is the most important form of deep learning model, and it includes layers such as fully connected, convolutional, and pooling ones. CNN is frequently utilized for reasons relating to the extraction of features and categorization. The CNN model is recognized as one of the most successful applications of deep learning. By the utilization of deep convolutional networks and nonlinearity, it can immediately learn both local and spatial features and patterns from unprocessed input, which may include photographs, movies, texts, and sounds. CNN is now the class of models that are used for picture recognition and classification the most frequently. One of the primary advantages of using CNN is that, in comparison to other classification algorithms, it calls for a great deal less time to be spent on the preprocessing stage. It analyses the incoming data, trains the model, and then automatically extracts the critical information to enhance categorization. A CNN algorithm's primary goal is to download data in a controlled fashion without sacrificing crucial details for comprehending what the data means—because of this, working with enormous data sets is possible. Essentially, CNN is made up of three layers. The complexity of the problem domain determines the number of layers. There are a lot more of these layers in complex applications. The general structure of CNN is described in Figure 3.1.

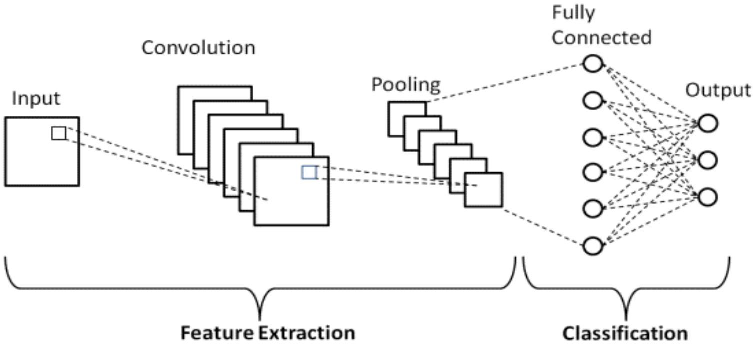

Figure 3.1 General structure of CNN

3.1.1 Convolutional layer:

The picture undergoes the application of a convolutional layer first, followed by a pooling layer, and then a fully connected layer for the final step. Three distinct kinds of layers are comprised in a convolutional neural network: the Convolutional Layer, the Pooling Layer, and the Soft Max Layer. Within the convolutional layer, the input picture is processed using several different kernels. A spatial invariance average or maximum operation is utilized by the pooling layer to reduce the overall size of the feature map [36]. The pooling layer and the convolutional layer are both included in the feature extraction module. The characteristics of the color, texture, and form are retrieved. In this particular piece of research, the function of the feature extractor is played by a Convolutional Neural Network. The input feature maps are organized into class values by the Softmax activation function, which is located in the Softmax layer. They start by convolving the entire picture using a variety of kernels and then use feature mapping at various stages along the way to provide several outputs of feature maps.

The general formula for convolution operations is obtained as follows:

$$y_j^l = f\left(\sum_{j=1}^{M_j^{l-1}} w_{ij} * x_i^l + b_j^l\right), \qquad j = 1,2,\ldots,M \tag{3.1}$$

The j^{th} feature map of the convolutional layer is represented as w_{ij}. In the j^{th} convolutional kernel of the current layer, the offset is defined as, b_j^l and the feature map of the upper layer is x_i^{l-1} and the symbol $*$ represents the convolutional operation. The batch size refers to the number of samples processed before updating the model. The quantity of epochs represents the total number of passes through all the training data. Among the available options, the rectified linear unit (ReLU) activation functions, tan*h*, and sigmoid are the parameters in CNN applications. Compared to the other parts, the ReLU function is much faster to compute while still producing good results.

$$f(x) = \begin{cases} x, & if \quad x > 0 \\ 0, & otherwise \end{cases} \tag{3.2}$$

3.1.2 Pooling layers:

The pooling layer reduces the size of the convolutional layer's output to lower the computational cost of the following network layers and avoid overfitting. Average and maximal pooling are the most used pooling algorithms [37]. This study chose the maximum pooling method as the down-sampling method because it allows the calculation to converge quickly. A 2:2 sub-sampling window is used equally by the pooling layers.

$$y_j^l = f\left(\frac{1}{m}\sum_{i=1}^{M_j^{l-1}} x_i^{l-1} + b_j^l\right) \tag{3.3}$$

The j^{th} feature map after poling is y_j^l. From the convolutional layer to the sampling layer, the window size is m and b_j^l is the bias function. Where the pooling layer function and the down-sampling process are $\sum_{i=1}^{M_j^{l-1}} x_i^{l-1}$.

The pooling layer and the convolutional layer are alternately connected. The number of extracted feature maps grows as the network depth increases while the size decreases. The extracted traits have more expressive potential.

3.1.3 Fully connected layers:

In neural networks, fully connected layers execute advanced reasoning. They're hidden behind the pooling and convolution layers [38]. The linked layer’s inputs are connected to the front layer's outputs. For classification operations, the fully connected layer translates the 2D feature map into a 1D feature vector. The following is the formula for calculating the connection layer:

$$h_{w,b}(X) = f\left(w^T x + b\right) \tag{3.4}$$

Where, $h_{w,b}(X)$ is the neuron output, x is the input eigenvector, w is the weight vector, b is the offset vector, f(•) is the activation function, and x is the input eigenvector. When the parameters are adjusted during training, a fixed proportion of neurons are disconnected to reduce over-fitting and improve the network's generalization capabilities.

3.2 Proposed Model Architecture

Multiple inputs from current systems are used to create the new system. In our example, we considered several factors when developing this system to accurately identify food items, such as fresh and damaged fruits. CNN, a deep learning technology, is employed in our system to create a novel model that can detect and identify the intended photos during the test and validation phases. Convolutional neural network techniques were covered in detail in Chapter 2. To achieve good accuracy, we created our system with multiple layers, a batch size of 32, and a kernel size of 3, and executed the model for 50 epochs and considered the better accuracy. In Figure 3.2, we can observe the complete architecture of the proposed model. In the diagram, the preliminary understanding of the training model is mentioned, nothing but the initial supply of the images belonging to a fresh and rotten category, the type of activation function used, the number of filters considered in each case, batch normalization and the Pooling layer as individual set in the training. Similarly, increasing the number of filters at every step to maintain good accuracy and also to overcome the problem of underfitting and overfitting. To extract characteristics from photos, filters are helpful. so that accuracy can increase, and the overfitting and underfitting issues do not affect the model. To solve the underfitting issue, hidden layers can be added, provided that the dropout or data augmentation concepts are applied to mitigate overfitting. There are two fully connected are used to identify the image properly by dropping some neurons in between. As our model uses multiple classes for training and testing, the activation function Softmax was utilized, whereas for binary classification Sigmoid function can be used for detecting the input images.

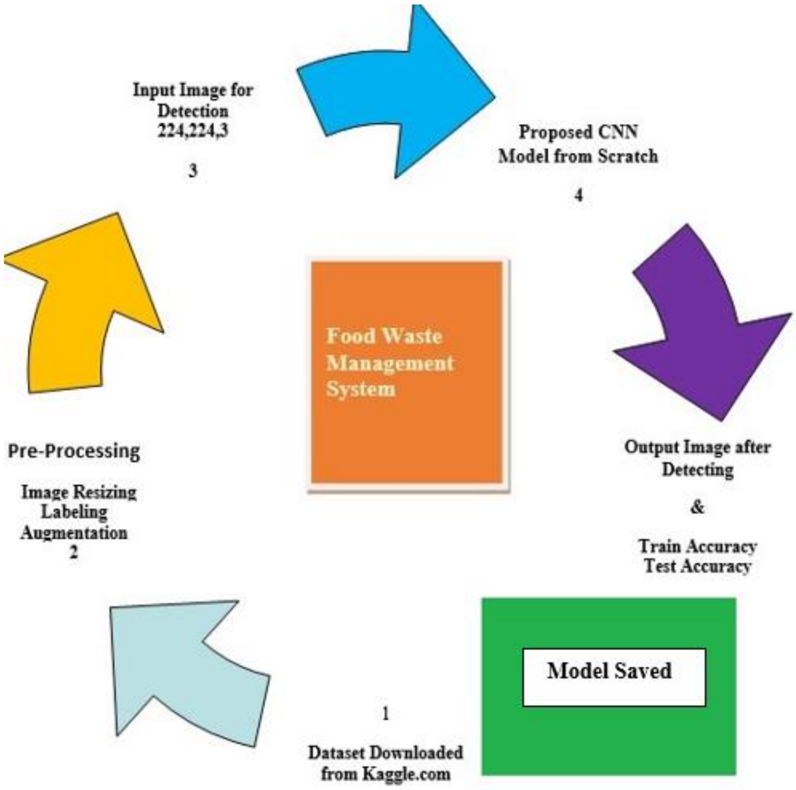

Figure 3.2 Proposed Model Block Diagram

In Figure 3.2, we can observe the complete idea of the detection and classification fruit of a single proposed model. The beginning stage is a selection of the data set and downloading from the source Kaggle.com and then moving to Pre-processing of the data set with augmentation. In the third stage, building the new model from scratch by using Convolutional Neural Networks by giving the input image size, and finally after extracting the features the limited number of neurons will be supplied to the fully connected layers for pattern detection. In the training, we need to note the accuracies for evaluating the model performance and finally, the model is saved.

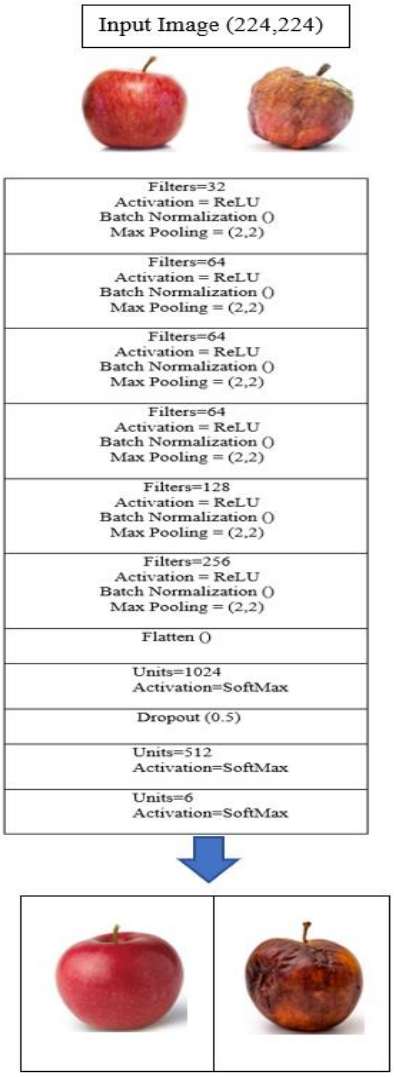

Figure 3.3 Proposed Model Architecture

We can see the entire process of how the system was created from inception in the block diagram of our system. First, 8400 additional photos are added using data gathered from Kaggle.com.This model detecting and classifying fresh and rotten fruits has done well.

3.3 Dataset Preparation

The dataset details are collected from https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification, in which the dataset contains six classes, including three fresh and three rotten fruits. The dataset image consists of 8400 images, and the dataset is divided into training and testing data [62].

Table 3.1: Sample image classes based on fresh and rotten fruits based on the Kaggle dataset

Name of the Fruits	Fresh	Rotten
Apple		
		
		
		

Orange		
		
		
		
Banana		
		
		

3.4 Data Pre-processing

Initially, the pre-processing step is carried out to remove the noises, and both image resizing and labeling are performed. The low contrast problem in fruit images is enhanced with the help of Contrast Limited Adaptive Histogram Equalization (CLAHE). The performance of CLAHE outperformed better results of Histogram Equalization (HE) as well as Adaptive Histogram Equalization (AHE) [32-34]. Further, the image noise levels are removed, thereby obtaining the desired results of pre-processed images. The histogram intensity height relates to the contrast enhancement of fruit images. The variations in color intensities are image contrast [35], which is expressed as follows:

$$CMR = \frac{Max_t - Min_t}{Max_t + Min_t} \tag{3.4}$$

The contrast measure range (CMR) tends to the fields [0, 1]. The maximum and minimum intensity values are described as Max_t and Min_t .

3.5 Labeling

In every class, all images are labeled to improve the model's chances of recognition and maintain uniformity in the dataset, as mentioned below. In the data set, all images of each class are resized to 224x224 using Python Imaging Library (PIL) and saved to the specified folder.

Table 3.2 Number of images in each class for training

S. No	Class	No of images	Label_train	Label_test
1	Fresh Apples	1260	FA1..1260	FA1..140
2	Fresh Oranges	1260	FreshO1..1260	FreshO1..140
3	Fresh Bananas	1260	FB1..1260	FB1..140
4	Rotten Apples	140	Rotten1..1260	Rotten1..140
5	Rotten Oranges	140	RottenO1..1260	RottenO1..140
6	Rotten Bananas	140	RottenB1...1260	RottenB1...140
	Total	8400		

In Table 3.2, we can observe the labeling of different classes for training and testing to build the model from scratch. The main advantage of this is that the model can be understood easily while training, and it will be helpful in the case of testing also once the training is completed. In another case, there will be clarity about the images in the data set. In turn, the prediction of the images can be made safely, and we may get the correct accuracy. In some cases, there is a chance of reducing underfitting and overfitting during the entire training and testing phase.

3.6 Experimental Setup

The work for the research was carried out using Jupiter Notebook, which is located on Anaconda Navigator. Before moving on to the coding portion of the project, many essential Python libraries, such as TensorFlow and Keras, were incorporated. Working with such a large number of photos in the dataset simultaneously brings about an increase in the complexity of the system configuration. The batch size always influences the execution time, number of layers, samples, and system setup. CPU systems require more time to run than GPU systems do. However, the cost of the system rises from the CPU to the GPU. Similarly, more than small data sets are required to obtain reliable predictions and cannot be used to assess the model's performance. In our situation, the machine is equipped with an i7 processor, 4 GB of RAM, and an NVIDIA GEFORCE RTX3060 GPU.

Table 3.3 Simulation Parameters

Batch Size	32
Epochs	50
Image size	224
Number of Layers	11
Filters	3
Activation Function	ReLU & Softmax

For a better outcome, the input parameters are employed in the training process before training the model. the size of the image, the batch size, the kernel size, the number of convolution layers, the number of pooling layers, real layer connections, etc. [Table 3.3]. One of the key variables for improving model performance and training is batch size. More memory and time will be used for each epoch when the batch size is increased. In turn, when we compare smaller batch sizes to larger ones, the input image's feature detection will perform well. While training, we experimented with various batch sizes; however, batch size 32 performed best. The model is trained with 7560 images and tested with 840 photos. The training accuracy was 98.4%, and the test accuracy was 95.14%. We can also see the number of wrong and correct predictions once the confusion matrix is generated.

3.7 Accuracy:

In the training phase, we supplied all the images with precise dimensions like size, label, and division images in all six classes. The model is trained with more ideas to detect damaged and fresh fruit. Initially, we arranged the platform by installing all the required packages and loading the dataset folder and also setting the training images path properly (Desktop/Dataset(224-224)/train), and class_mode is designated as "categorical." This can be loaded by using the train. flow_from_directory command in Python. After uploading the dataset into the Jupiter notebook, we can check the indices of the classes as shown below:

train_set.class_indices

```
{'fresh apples: 0, 'fresh banana': 1, 'fresh oranges': 2, 'rotten
apples': 3,' rotten banana': 4, 'rotten oranges': 5}
```

While training the model number of steps for each is calculated as follows:

steps_per_epoch = train_data_size//BATCH_SIZE

So, for every epoch, the number of steps => steps_per_epoch = 7560//32

= 236

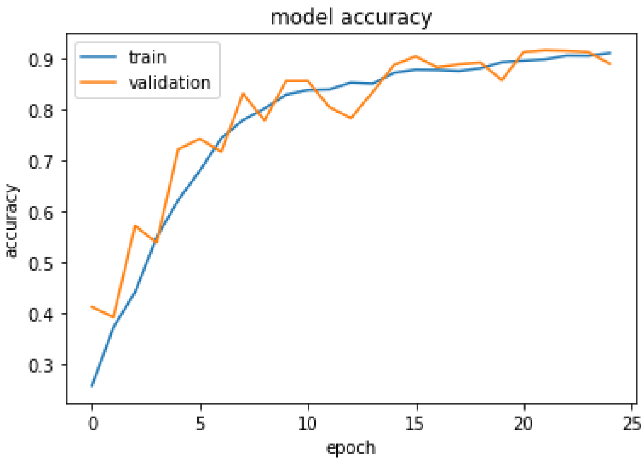

Figure 3.4 Model Accuracy at 25 epochs

In Figure 3.4, we are seeing the result of accuracy under the specified parameters for 25 epochs. As in this work, we used the GPU machine for each epoch which took less time when compared to the CPU machine. This is the result we mentioned after verifying the values for different values. One curve represents the train and the other one represents the validation result.

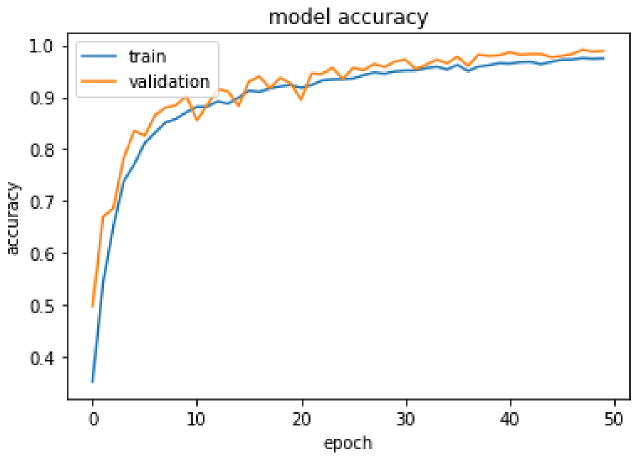

Figure 3.5 Model Accuracy at 50 epochs

Figure 3.5 shows the outcome of accuracy for 50 epochs using the given parameters. Since the GPU computer was used for each epoch in our work, it ran faster than the CPU machine. After confirming the values for various parameters, we came to the conclusion we suggested. The train is represented by one curve, while the validation result is represented by the other curve. From Figures 3.5 and 3.6, we can understand that the model gives good accuracy at the 50th epoch compared with the 25th epoch. So, one of the objectives is to propose a model, which should perform well at detecting fresh or rotten fruit.

3.8 Loss:

We provided the photographs with precise measurements during the testing process, including size, label, and division images across all six classes. More photos are used to evaluate the model's ability to distinguish between fresh and damaged fruit. The class mode is set to "categorical," the photographs are loaded, and they are also designated as the testing images (Desktop/Dataset(224-224)/test). The “test. flow” from the directory command in Python can be used to load this. We can examine the class indices as shown below after uploading the dataset to the Jupiter notebook:

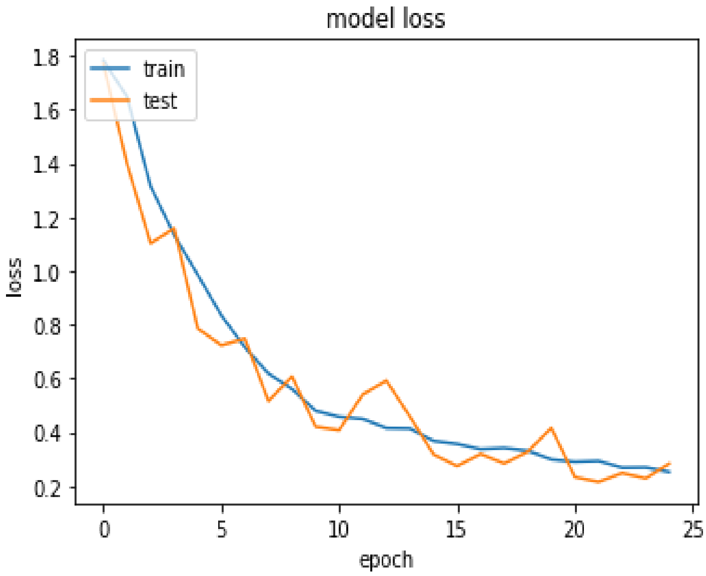

Figure 3.6 Model loss for 25 epochs

The loss value always should be less in the model building then we can achieve better accuracy otherwise we can’t get accurate results. In our work, we have taken special observation to decrease the loss in the training and testing under different values. In such a case, we can see the result as mentioned in Figure 3.6 and it is noted at the 25th epoch.

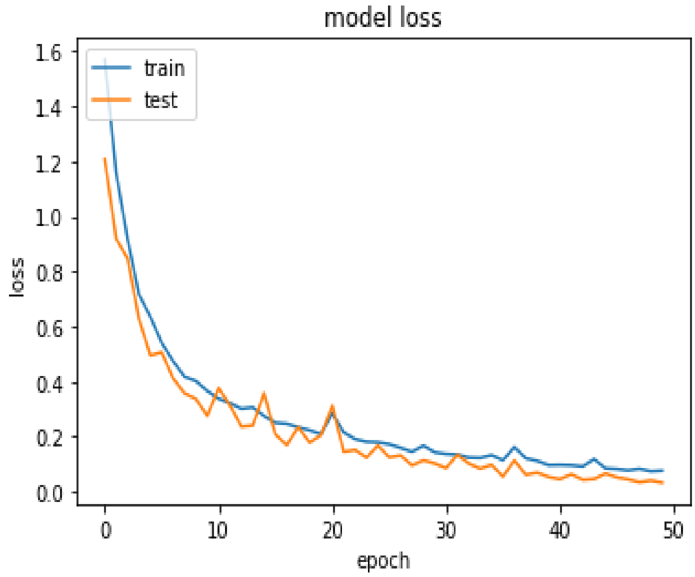

Figure 3.7 Model loss at 50 epochs

To develop a model with better accuracy, the loss value should constantly be lower otherwise, we cannot provide an accurate result. We have made unique observations in our work to reduce loss in training and testing for various values. In this situation, we can observe the outcome shown in Figure 3.7, which is documented at the 50th epoch.

3.9 Confusion Matrix:

In the process of attempting to resolve classification challenges, confusion matrices are a measurement that is frequently utilized. Problems concerning binary classification as well as those involving multiclass classification can be handled using it. Confusion matrices are a common kind of evaluation that is used in the process of attempting to solve classification issues. It is possible to utilize it to address the challenges posed by binary classification as well as those posed by multiclass classification.

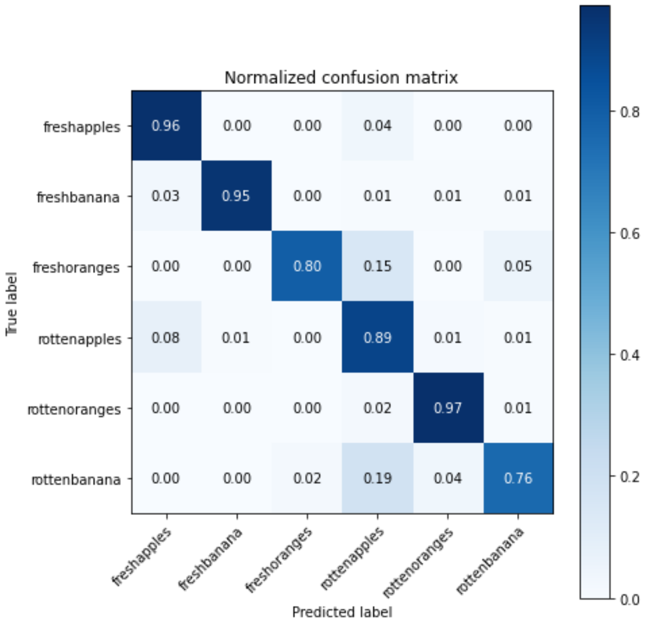

Figure 3.8 Confusion Matrix at 25 Epochs

The confusion matrix is generated to understand the correct and wrong classified images, then we can able to check with different values. In Figure 3.8, we have observed the predictions class-wise with percentages at the 25th epoch.

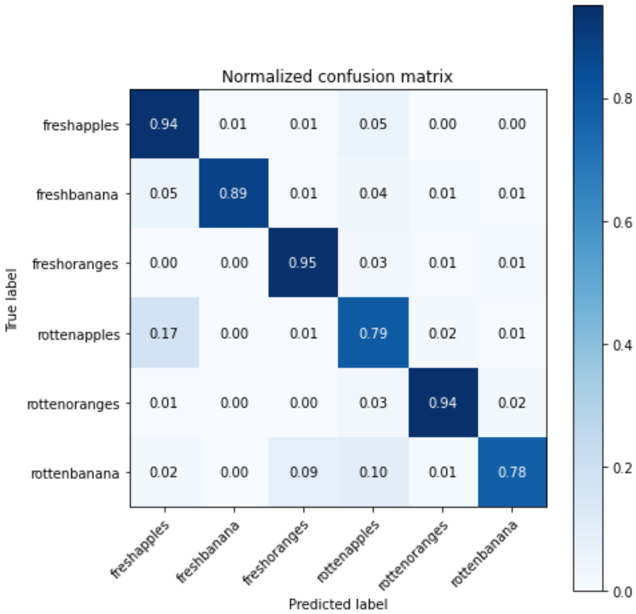

Figure 3.9 Confusion Matrix at 50 Epochs

The confusion matrix is created to help distinguish between correctly and incorrectly classified photos, after which we can do a check using various values. Figure 3.9 shows the predictions for each class at the 50th epoch, with percentages.

3.10 Classification Report

The correctly categorized TP values, FP values in the appropriate class, when they should be in another type, FN values in another class when they should be in the proper category, and correctly classified TN values in the other category, are all represented in the confusion matrix. Four fundamental properties (numbers) make up the confusion matrix, which provides the classifier's measurement parameters. These are the four numbers:

1. TP (True Positive): The number of fruits that have been correctly identified as having damaged fruits, or fruits with a defect, is represented by this number.
2. TN (True Negative): TN is the proportion of accurately identified nutritious fruits.
3. FP (False Positive): FP refers to the number of fruits incorrectly labeled as having a problem but healthy.
4. FN (False Negative): FN refers to the number of fruits incorrectly labeled as healthy but damaged.

Table 3.4 Precision, Recall, and F1-Score (Performance Measures)

Class_Type	Precision	Recall	F1-Score
Fresh apples	0.95	0.94	0.94
Fresh banana	0.96	0.91	0.96
Fresh oranges	0.99	0.99	0.98
Rotten apples	0.96	0.99	0.98
Rotten oranges	0.92	1	0.96
Rotten banana	0.99	0.97	0.95
Classification_Accuracy			0.95

Accuracy, precision, recall, and F1 score are algorithm performance metrics derived from the previously mentioned TP, TN, FP, and FN.

The ratio of correctly classified fruits (TP+TN) to all fruits (TP+TN+FP+FN) is used to measure an algorithm's accuracy.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3.5}$$

The ratio of correctly identified disease fruits (TP) to all patients expected to have the disease (TP+FP) is used to measure an algorithm's precision.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3.6}$$

The ratio of correctly diagnosed diseased patients (TP) to the total number of patients with the disease is known as the recall metric.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3.7}$$

How many fruits have been identified as having the condition is thought to be the reason for the recall. The recall is another name for the sensitivity F1 score and the F Measure. The F1 score indicates the balance between memory and precision.

$$\text{F1-Score} = \frac{2*Precision*Recall}{Precision+Recall} \tag{3.8}$$

3.11 Hyper Parameters Tuned

Hyperparameters are used to construct the proper network structure in building the model to detect and classify the images in our research work. At the same time, we can’t fix the values exactly for our problem. It will be done on the trial-and-error method to finalize for which values our model performs better and gives the accurate result. In Table 3.5, different values are checked given optimal values.

Table 3.5 Hyper Parameters verified on our model

Hyperparameters	**Ranges**	**Optimal values**
Dropout rate	[0.1, 0.2, 0.3, 0.5]	0.5
Kernel size of convolution	3,5	3
Epochs	[25,50]	50
Batch size	[32,64]	32
Weight	[0.0001, 0.001, 0.01]	0.001
Learning rate	[0.001, 0.01, 0.1]	0.01
Optimizer	Adam	
Loss function	Cross-Entropy	

3.11.1 Optimizer

Another crucial consideration is the choice of an optimizer that enhances the model's efficiency. It updates the weight parameter, which lowers the loss function. We aim to lessen neural network loss by modifying the network's parameters. By contrasting absolute and predicted values, the loss function of the neural network is evaluated. Four optimizers are assessed to determine the best optimizer, and their accuracy levels are compared. In the work that has been given, four optimizers have been used: stochastic gradient descent (SGD), Adam, Adagrad, and RMSprop. According to analysis, Adam optimizer, which provides an accuracy of 95.14%, is the best optimizer, whereas RMSprop, SGD, and Adagrad give an accuracy of 82.09%, 77.43%, and 71.65%, respectively [Figure 3.10].

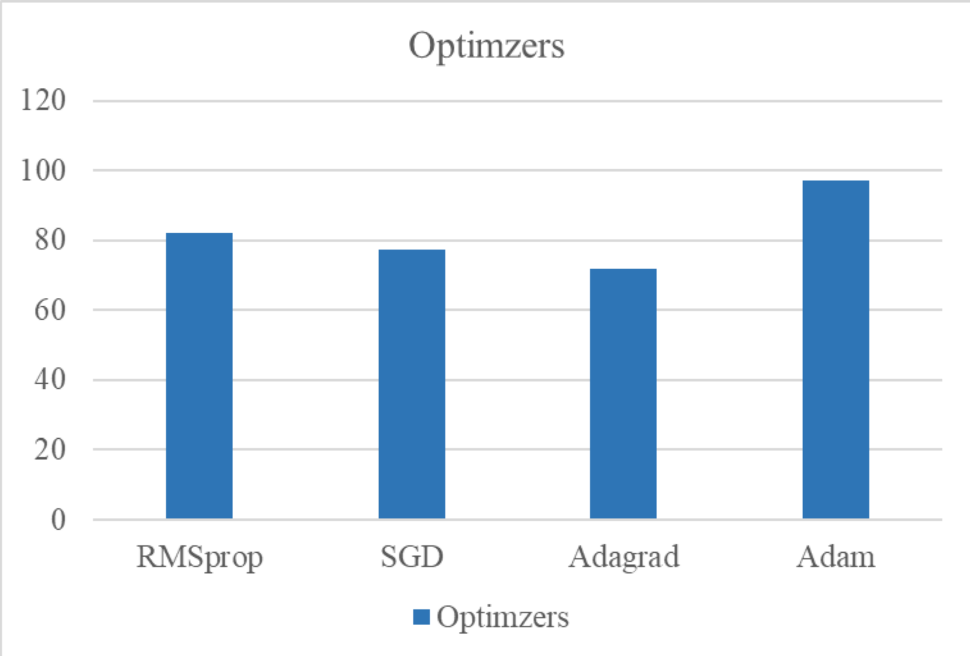

Figure 3.10 Accuracies at Different Optimizers

3.11.2 Learning Rate

Weights are updated to a certain extent during neural network training. The learning rate is known as this. The learning rate significantly impacts the effectiveness of CNN models. It has a range of 0.0 to 1.0. We employed four learning rates to train our model and examined how accuracy varied. The study used four learning rates: 0.1, 0.01, 0.001, and 0.0001.

In our study, we adopt cross-entropy as the default loss function for multi-classification. It computes the average difference between the actual and predicted probability distributions for each class in the problem.

3.12 Summary:

This study proposed a novel deep-learning model for fresh and damaged fruit image classification. The dataset images were collected from https://www.kaggle.com/datasets/sriramr/fruits-fresh-and-rotten-for-classification. It contains 8400 images with six classes, including fresh and rotten fruits of apples, bananas, and oranges. From this, 60% of images were used for training, 20% for validation, and the remaining 20% for the image testing process. The pre-processing step is handled to enhance the contrast level and remove noise from the input images. After that, the color, texture, and shape data have been extracted by the CNN model. Also, the fruit image classification is performed. Still, the classification performance is decreased due to the shortcoming of hyperparameter tuning in terms of the number of hidden layers, dropout rate, weights, learning rate, size of the stride, and kernels of the CNN model. Hence, the novel model tunes the hyperparameters of CNN effectively. Finally, the proposed CNN effectively classifies fresh and damaged fruits, thereby managing food waste. A classification accuracy of 95.14% is obtained.

Chapter 4

Ensemble Approach to detect and classify Fresh and Damaged Fruit

This chapter covers the methodology of an ensemble model to detect and classify fresh and damaged fruit. There is a need for an ensemble model when compared with a single model in the same case to understand which is better. Some of the pre-trained models are taken as support in building the proposed ensemble model. At the same time, the proposed ensemble models are also compared with some existing models to show the impact of our model in detecting and classifying the model. To build our model, tuning parameters, data set, and other technical support are taken as per the need. These all details are discussed throughout the chapter.

4.0 Ensembling

In both supervised and unsupervised learning scenarios, ensembles of learnings combine their outputs, learning algorithms, or various views on the data in some way to provide more accurate and reliable predictions. By mixing numerous models, ensemble learning enhances results. Compared to using a single model, this technique enables the generation of superior prediction performance. The majority vote ensemble only illustrates this idea. The class that obtains the most votes is the one that the ensemble predicts. It explores the conclusions reached by various learning machines. Many taxonomies of ensemble methods have been provided to assist academics and practitioners in organizing themselves and creating innovative concepts and procedures. Depending on the fundamental classification criterion employed, there are many ways to categorize and evaluate combination approaches. Suppose the primary criterion is how the input patterns are represented. In that case, we may distinguish between two enormous groups, one of which uses the exact representation as the inputs, and the other uses a different model.

With this general technique, the ensemble's output is equivalent to the production of the group of base learners' best base classifier for a given input. In a larger sense, it is also possible to select a subset of base classifiers. In this situation, we must decide whether to use one of the desired outputs as the collective output or to combine the production of the base learners using, for example, one of the ensemble fusion algorithms outlined in the preceding section. To create an ensemble selection technique, we must choose a selection strategy, determine how to make the individual classifiers, and assess how well each classifier performs given a specific input. Due to the potential increase in processing cost, deep neural network building is not accessible. After all, training several neural networks would be necessary. Implicit/explicit ensembles are used to implement the paradoxical goal of making a single model behave as a collection of training many neural networks. These ensembles incur no additional cost or the least amount of extra cost imaginable during the process. In this case, the training times for an ensemble and a single model are equal. Because implicit ensembles share the model parameters, the single network closely resembles the model average of the collective models during testing. Explicit ensembles, on the other hand, do not exchange model parameters. The ensemble output is a collection of forecasts made by the ensemble models using various methods, such as majority voting, averaging, and other methods. The explicit and implicit approaches use a single network to produce ensembles at the price of the diversity of the base models because it is likely that all of the models' lower-level attributes will be the same. An ensemble could be more variable thanks to many neural networks with various initializations and loss functions. To address branching-based deep models, branch the network to boost variability. An ensemble network is created when concealed nodes are freely deleted from a network during training.

4.1 Majority Voting Ensemble Classifier

In our work, the final decision-making process is a majority vote ensemble. The first step in the majority voting method is to tally the votes cast for each base classifier. For the anticipated class label, the majority of votes are calculated. The majority-voted base classifier prediction receives the final prediction. It forecasts the final labels as the label with the majority of votes rather than taking the average of the probability outcomes. Combining the results of the essential learners is majority voting. However, majority voting counts the votes of the base learners. Because the influence is lessened by the majority vote count, majority voting is less biased towards the result of a specific base learner than averaging. The development of computer vision systems offers a chance to expand image classification research and applications in agriculture. Classifying rotten and fresh fruits is a crucial responsibility and a significant issue in the agriculture sector since, if improperly categorized, decaying fruits can damage new crops. To save labor expenses associated with rejecting rotting fruits at the production stage, it is necessary to have an automated system that can precisely determine the fruit's freshness, especially for the harvesting robots that pick only fresh fruits. The method can be used in supermarkets to improve the fruit sorting process by quickly eliminating rotten fruits. To increase classification accuracy, our research includes a combination of previously developed CNN models for assessing fruit quality. We created and put into practice an ensemble technique that combines the characteristics of three CNN models with various architectural styles to classify the fresh and rotten fruit. We conducted thorough tests for different fruit categories using multiple methodologies and other methods, employing a dataset that comprised fresh and rotting fruits. We showed that the suggested ensemble model works better than current methods for classifying the fresh and damaged fruit. The accuracy offered by each combination can be assessed by contrasting the averages of the various models shown in Figure 4.1 when comparing one variety to another.

In this proposed work an ensemble method based on transfer learning to classify fruit freshness by combining the bottleneck characteristics of three deep convolutional neural networks with different pre-trained architectures. Additionally, we provide a multi-task learning system that employs fruit-type information to improve fruit freshness classification performance. The research we conducted was systematically evaluated using datasets from the Kaggle website that included both fresh and rotting fruits.

4.2 Transfer learning

Transferring the knowledge found in various but related source domains, transfer learning tries to improve the performance of target learners on target domains. By doing this, the reliance on a significant amount of target domain data can be lessened for creating target learners. Transfer learning has become a promising area in machine learning because of the numerous application possibilities [72]. A larger dataset often produces more accurate outcomes for CNN than a smaller one. When it is not possible to create a big training dataset, transfer learning can be employed. In Figure 4.1, the idea of transfer learning is demonstrated, where a model that has been pre-trained on big datasets (ILVSR [65]) can be applied to a relatively smaller dataset.

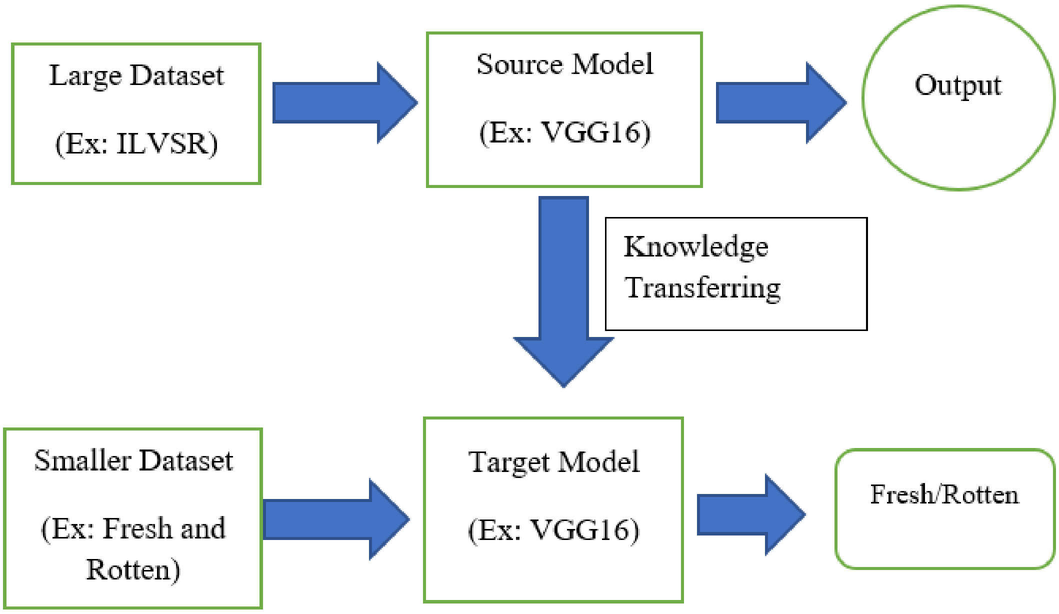

Figure 4.1 Concept of Transfer Learning

4.3 Pre-trained convolutional neural networks

VGG [65], AlexNet [66], Dense Net [67], ResNet [68], Inception V3 [70], MobileNet V2 [69], and Shuffle Net V2 [72] are some of the pre-trained CNNs that were evaluated in our tests. Here is a brief description of these pre-trained CNNs.

4.3.1 VGG

In this pre-trained model, we have two categories VGG16 and VGG19. VGG16 is one of the popular neural network architectures associated with the ILVSR dataset, and it supports a maximum of 19 layers. The number of filters used in this model is 3x3. At the same time, the pooling layer size is about 2x2.In this model, the input image size is 224x224. In the figure, we can understand easily how the models are built on different parameters.

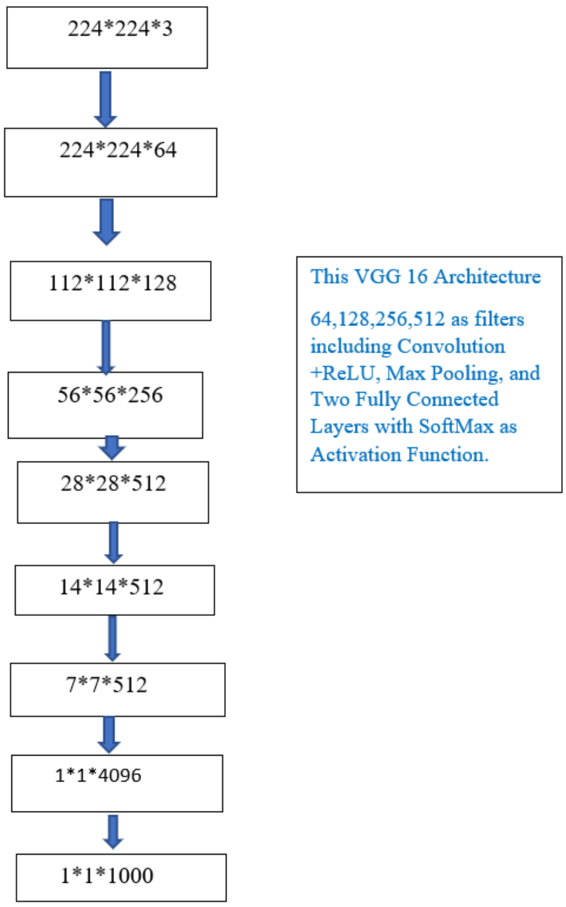

Figure 4.2 VGG16 Architecture

The number of convolutional layers, pooling layers, and fully connected layers will be taken while training the dataset. In this case, this is a pre-trained model designed in association with a larger data set called ILVSR. Here 64, 128,512 filters are used by default associating with the Max pooling layer and 1000 neurons taken in the last layer of the complete design.

4.3.2 AlexNet

AlexNet is the 8-layer architecture of the convolutional neural network. This model contains about five convolutional layers and three dense layers. In addition to these, max-pooling layers cover up the architecture. In this architecture, the ReLU activation function is used, and the image size of the input is about 224x224.

4.3.3 Dense Net

Dense Net, abbreviated as Dense Convolutional Neural Network, was proposed by Facebook.DenseNet connects all layers directly by combining them. DenseNet-121 and DenseNet-169 both take 224x224 pixel pictures as input.

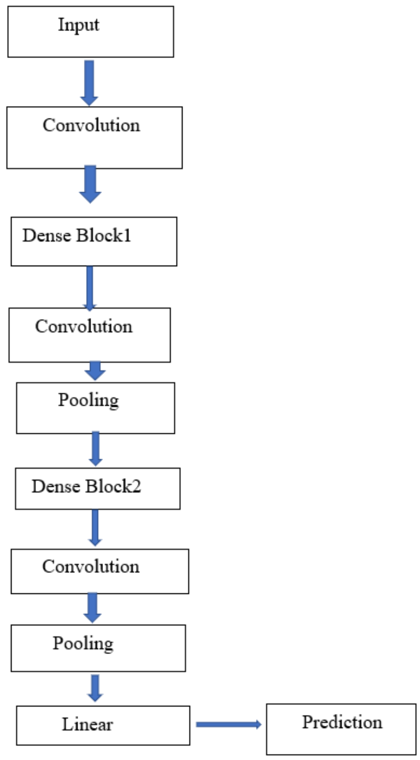

Figure 4.3 Dense Basic Architecture

In the figure, we can observe the basic architecture consists of multiple layers including convolutional, pooling, and dense blocks at every stage. This model consists two of categories both following the same architecture with different layers. In this model, each layer will receive the data from previous layers. Because each layer receives feature maps from all preceding layers the network becomes thinner and the number of channels can be reduced. Due to this, we can expect higher computational efficiency.

4.3.4 ResNet

ResNet was proposed by Microsoft Research in the year 2015 and associated with ILSVR. Based on the number of layers in the residual network, ResNet comes in various forms. For classifying the freshness of fruit, we employ ResNet-50 and ResNet-101. ResNet's input layer can take 224x224 pixel pictures.

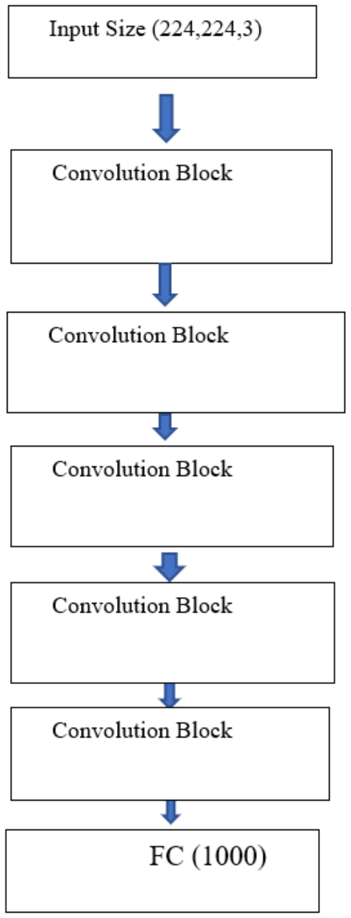

Figure 4.4 RESNET Basic Architecture

This architecture is becoming popular due to there are many pitfalls in the existing ones in terms of complexity, memory, and other factors. Resnet-50 is a variant of 48 convolutional layers, one max-pooling layer, and one Average Pooling Layer. Whereas Resnet-151 is a deep one with 151 layers. In the same manner, we have many architectures developed in the difference of multiple parameters and accuracy.

4.3.5 MobileNet

Google suggested MobileNet in 2016. With the help of depth-wise separable convolutions, Mobile Net's lightweight CNN architecture can compute FLOPs and parameter counts more efficiently. Initial research led to the development of depth-wise separable convolutions, which split a conventional convolution into two parts: a point-wise convolution that employs a 1x1 convolution to capture the channel-wise relationship of features and a depth-wise convolution that employs a 3x3 convolution to extract the spatial relationship of parts. Both of these convolutions were developed by depth-wise separable convolutions. The second iteration of MobileNet suggested two optimal methods. These were the reverse residual structure, in which the shortcut connections are between the thin layers, and the linear bottlenecks, which remove non-linearities in the thin layers. Both of these methods remove non-linearities in the network. Because MobileNet V2 is so widely used, we thought it would be a good choice to utilize it in our experiment. The size of the input data is 224 by 224.

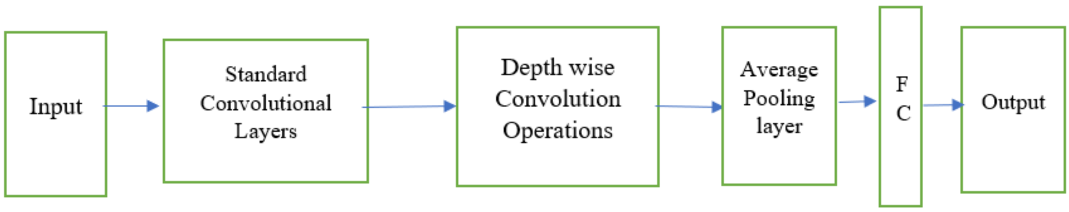

Figure 4.5 MobileNet Basic Architecture

MobileNet was developed using an algorithm called as that generates lightweight deep neural networks by making use of context-separable convolutions. We input and combine latency and accuracy with the help of two straightforward global hyper-parameters that we introduce. These hyper-parameters give the model builder the ability to choose the model that is the proper size for their application, taking into account the constraints that are imposed by the problem. We address in-depth research on resource and accuracy trade-offs, and we exhibit good performance on ImageNet classification when compared to the performance of other popular models.

4.3.6 Inception

Google launched GoogLeNet in 2014, the first version of Inception. Google Net won the 2014 ILSVR classification task contest. GoogLeNet expands the network's width and depth while keeping computation cost constant. In GoogLeNet, the feature's multi-scale information is collected using filters with 1x1, 3x3, and 5x5 pixels in various branches. The architecture of Inception V2 and V3 is similar. Convolutions with a large filter size are factorized into smaller convolutions in Inception V3. Additionally, it converts regular convolutions into asymmetric convolutions by spatial decomposition. For instance, instead of 3x3 filters, it uses 1x3 filters followed by 3x1 filters. We consider Inceptionv3 for our work, and the input size is 299x299.

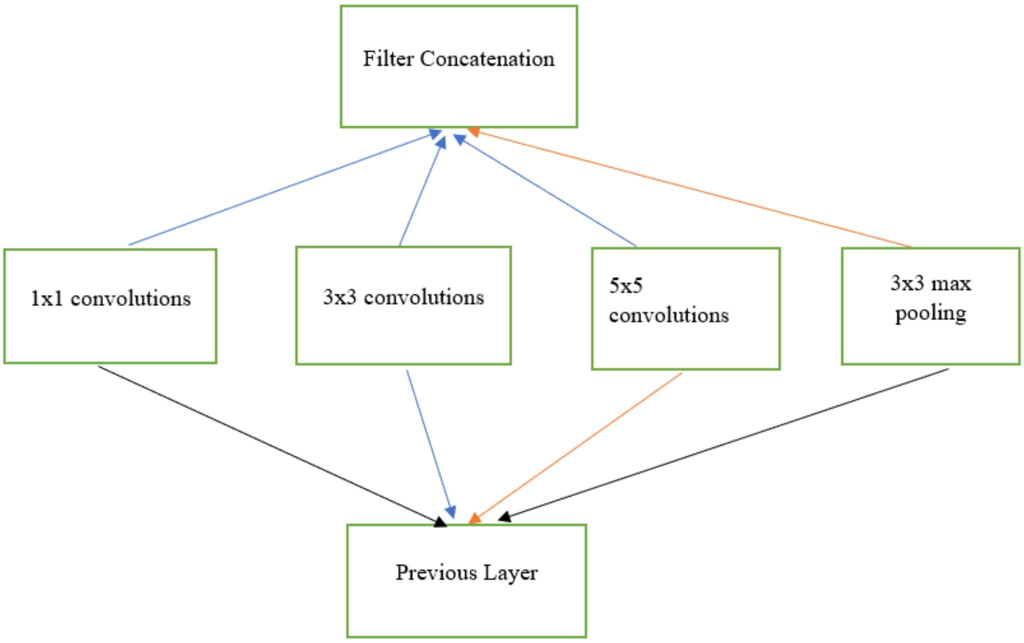

Figure 4.6 Inception Module

We offer a deep convolutional neural network structure called "Inception" that, in the 2014 ImageNet Large-Scale Visual Recognition Challenge, set a new standard for classification and detection (ILSVRC 2014). This architecture's main distinguishing feature is the improved exploitation of the network's computing resources.

4.3.7 Shuffle Net

A CNN architecture that is computationally effective and optimized for mobile platforms is called Shuffle Net. It has two operations: channel shuffle and point-wise group convolution. The depth-wise separable convolution technique with a 3x3 kernel lowers the computing cost. The purpose of the channel shuffle operation is to facilitate accurate information exchange between various channels and groups of channels. Shuffle Net's second iteration also introduces a highly effective unit that lowers memory access costs.

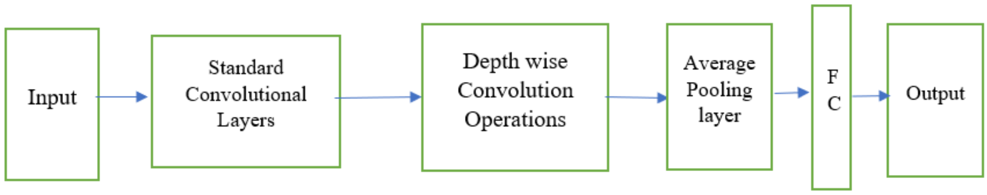

Figure 4.7 Shuffle Net Unit Basic Architecture

Shuffle Net V2 was our choice for the experiment due to its widespread use. Shuffle Net's input layer can handle 224x224 pixel pictures.

4.4 Proposed Ensemble Method

This section provides an overview of the architectural foundation of the recommended ensemble method. After that, in the parts that follow, we will go into the specifics of three factors that are quite important. The entire architecture of our proposed ensemble model may be depicted in Fig.4.8. The image enhancement component does its work first on the input pictures (Section 4.4.1). In the second stage, enhanced pictures are used as input for three pre-trained neural networks called ResNet-50, DenseNet, and VGG19. Following this, the extracted features from the three networks are combined in an ensemble step. (For further information, see Section 4.4.) A composite feature is fed into linear layers as part of the third stage of our multi-task learning system for categorizing fruit and freshness. By merging many independent models into a single predictive model, ensemble learning tries to increase the model's performance and reduce the risk of selecting a single model with a bad performance.

We choose ResNet-50, VGG16, and Dense Net as feature extractors in our ensemble model since their combined performance in a single proposed model indicates they function well [Chapter 5]. We also use a transfer learning-based methodology since it is often difficult to train convolutional neural networks like ResNet-50, VGG16, and Dense Net from scratch. We use the weights of pre-trained ResNet-50, VGG16, and Dense Net to extract the features of input photos. In our multi-task learning architecture for fruit and freshness classification, we concatenate two bottleneck characteristics from three pre-trained networks (ResNet-50, VGG16, and Dense Net) into one sequence and then supply to linear layers.

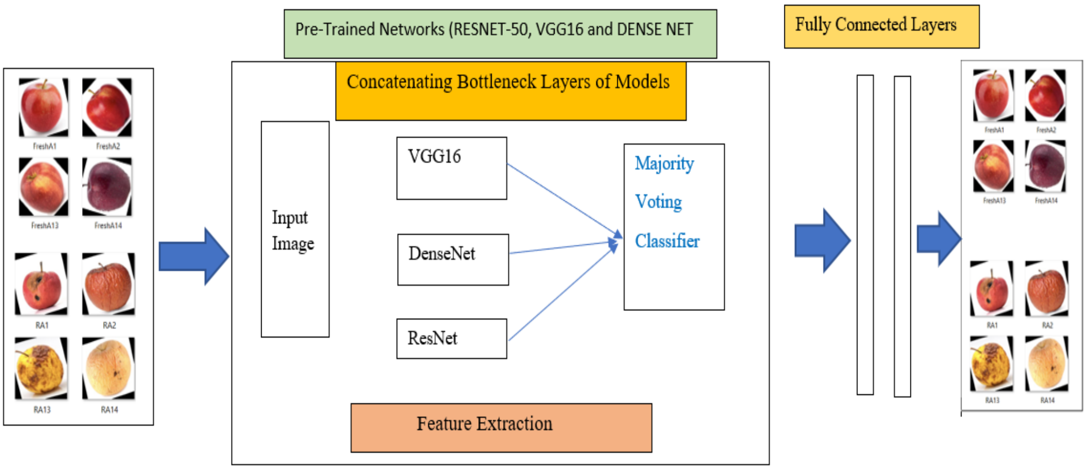

Figure 4.8 Proposed Ensemble Method Architecture

In addition to adopting a majority vote classifier to determine the model's final performance, our method combined three models. Even more parameters are used in the training as discussed in the chapter. Therefore, our ensemble model suggestion aims to provide a better solution to the problem that my investigation brought to light.

4.4.1 Dataset:

The dataset, which consists of six classes three are Fresh and three of which are Rotten—was taken from Kaggle. Test data, train data, and validation data are the three types. The total number of images utilized was around 8400; 80% of the photos from each class were used to train the model, and 10% were used. Sample Images are shown in [Fig.4.9, Fig.4.10].

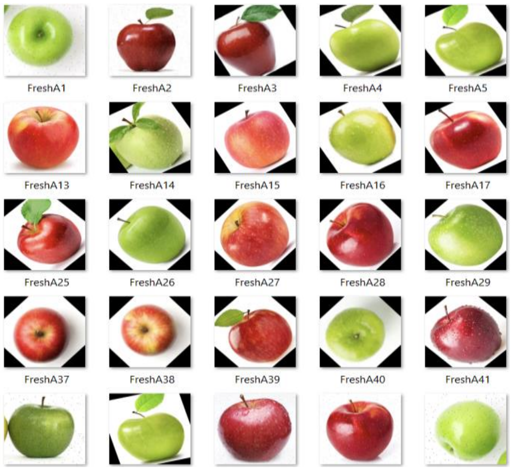

Figure 4.9 Fresh Apple Images from the data set.

Figure4.10 Rotten Apple Images from the data set.

4.4.2 Image Augmentation

It was previously noted that a significant amount of training data is necessary for CNNs to function properly. Having said that, the size of our fruit dataset is not particularly large. This problem may be handled by employing methods of image augmentation to extend the scope of the relatively small dataset. There have been indications that the accuracy of the classification performed by the deep learning model can be improved by using previously collected data rather than by acquiring fresh data. At the image augmentation stage of our project, we used two different augmentation approaches to produce additional training sets (rotation and horizontal flipping). The image is rotated clockwise by an inclination between 0 and 360 degrees during the rotation procedure, which is used to improve photos.

4.5 Experimental Setup

The research was carried out using the Anaconda Navigator and Jupiter Notebook. Before beginning the coding portion, significant Python libraries like TensorFlow and Keras were also integrated. Due to dealing with a substantial number of images in the dataset, the system configuration is also increased simultaneously. The execution duration, the number of layers, samples, and system configuration are always influenced by the batch size. Running CPU systems takes longer than running GPU ones. The system's price increases from the CPU to the GPU. However, larger data sets are needed to produce accurate predictions, similar to how limited data sets cannot be utilized to evaluate the model's performance.

4.6 Classification Accuracy and Results

After tuning all hyperparameters, mentioned in Table [3.5], we noted the model’s accuracy for the proposed ensemble. It is clearly shown that classifying is better than the single proposed model. We have also depicted the confusion matrix to see the wrongly classified images from the given data set. In Figure 4.11, we can observe that about ten photographs are classified wrongly from the test data. Similarly, the percentage of accuracy can be observed in Figure 4.12 Accuracy percentage is achieved for the test data in the proposed ensemble model. The results are discussed in the below section.

4.6.1 Accuracy

We provided the photographs with precise measurements during the testing process, including size, label, and division images across all six classes. More photos are used to evaluate the model's ability to distinguish between fresh and damaged fruit. The class mode is set to "categorical," the photographs are loaded, and they are also designated as the testing images (Desktop/Dataset(224-224)/test). The “test. flow” from the directory command in Python can be used to load this. We can examine the class indices as shown below after uploading the dataset to the Jupiter notebook:

train_set.class_indices

```
{'fresh apples: 0, 'fresh banana': 1, 'fresh oranges': 2, 'rotten apples': 3,' rotten banana': 4, 'rotten oranges': 5}
```

While training the model number of steps for each is calculated as follows:

steps_per_epoch = train_data_size//BATCH_SIZE

So, for every epoch, the number of steps => steps_per_epoch = 7560//32

= 236

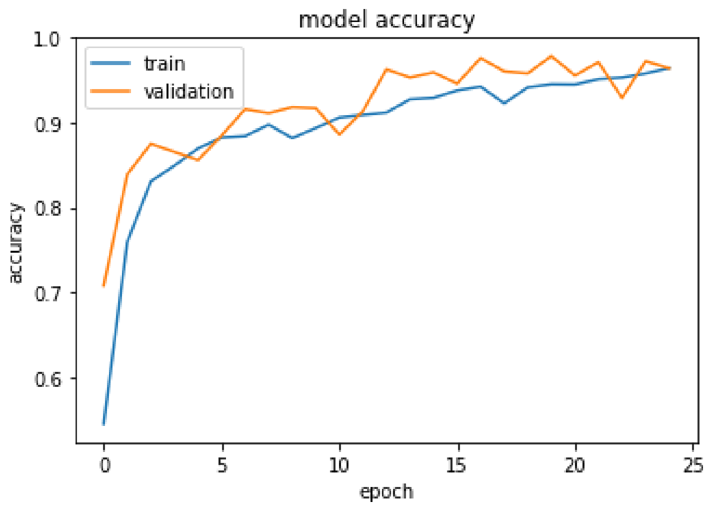

Figure 4.11 Model Accuracy at 25th epoch

Figure 4.11 shows the accuracy under the given settings for a total of 25 epochs. Since we used the GPU machine in this operation, it required less time for each epoch than the CPU machine. After confirming the values for various parameters, we came to the conclusion we suggested. The train is represented by one curve, while the validation result is represented by the other curve.

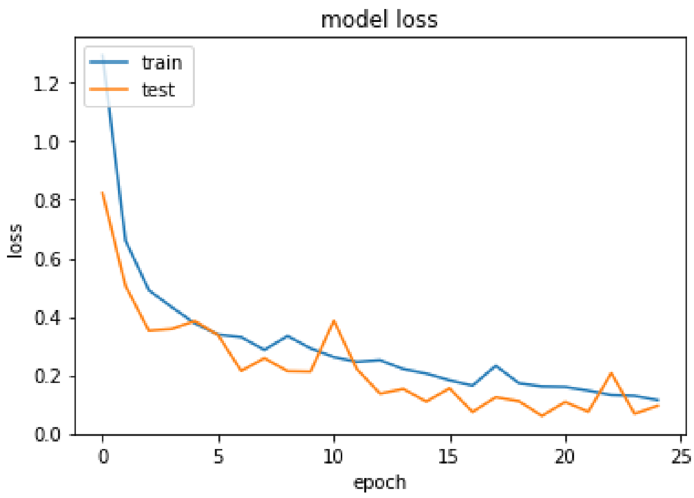

Figure 4.12 Model loss at the 25th epoch

The loss value should always be smaller to build a model with more precision otherwise, we cannot deliver an accurate result. In our efforts to minimize the loss in training and testing for various values, we have observed some unusual observations. In this case, the result depicted in Figure 4.12, which was recorded at the 25th epoch, is what we can see.

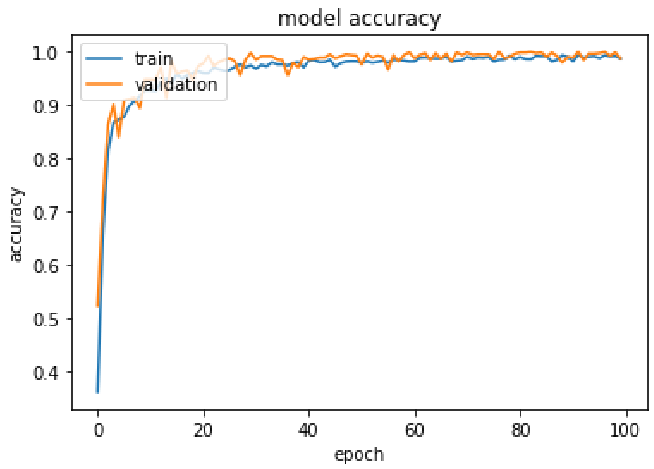

Figure 4.13 Model Accuracy at 50th epoch

Figure 4.13 displays the accuracy for a total of 100 epochs using the specified parameters. This procedure took less time per epoch than the CPU machine since the GPU machine was employed. We arrived at the conclusion we proposed after verifying the values for the relevant parameters. One curve represents the train, while the other curve represents the validation result.

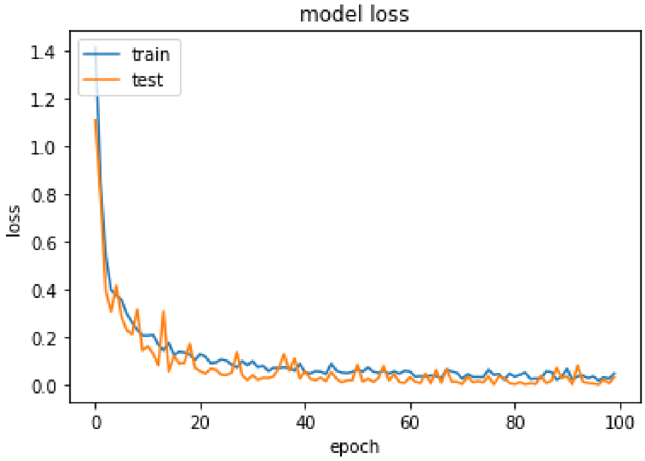

Figure 4.14 Model loss at the 100th epoch

To construct a model with more precision, the loss value should always be reduced otherwise, we cannot get an accurate result. We have made some surprising observations when attempting to limit loss in training and testing for various values. In this instance, we might observe the outcome shown in Figure 4.14, which was observed at the 100th epoch.

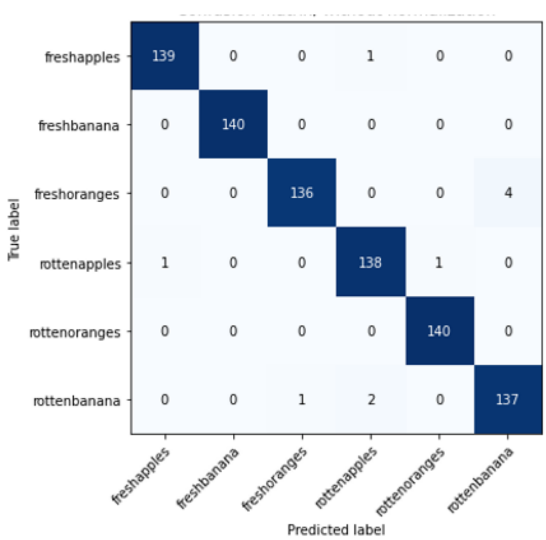

Figure 4.15 Confusion Matrix class predictions

The confusion matrix is created to help us distinguish between correctly and incorrectly categorized photos, after which we may do a check using various values. Figure 4.15 shows the predictions observed class-by-class with percentages at the 25th epoch.

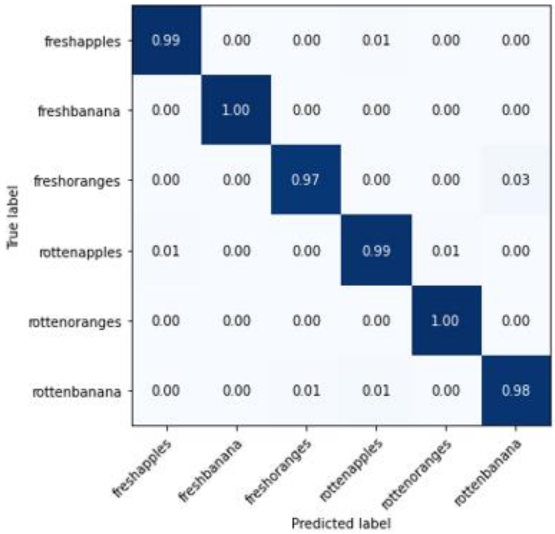

Figure 4.16 Confusion Matrix class prediction percentage

We may use a variety of variables to do a check after utilizing the confusion matrix to identify photographs that were properly and erroneously categorized. Figure 4.16 displays the percentage forecasts for each class at the 100th epoch.

4.7 Performance Measures

The F1 Score, Precision, Recall, and Average are used to evaluate the proposed ensemble model performance and generate the confusion matrix to know the wrongly classified images. The ratio of correctly classified fruits (TP+TN) to all fruits (TP+TN+FP+FN) is used to measure an algorithm's accuracy.

$$\text{Accuracy}=(TP+TN)/(TP+TN+FP+FN) \tag{4.1}$$

The ratio of correctly identified disease fruits (TP) to all patients expected to have the disease (TP+FP) is used to measure an algorithm's precision.

$$\text{Precision} = TP/(TP+FP) \tag{4.2}$$

The ratio of correctly diagnosed diseased patients (TP) to the total number of patients with the disease is known as the recall metric.

$$\text{Recall} = TP/(TP+FN) \qquad (4.3)$$

How many fruits have been identified as having the condition is thought to be the reason for the recall. The F1 score indicates the balance between memory and precision.

$$\text{F1-Score} = (2*\text{Precision}*\text{Recall})/(\text{Precision}+\text{Recall}) \qquad (4.4)$$

Table 4.1 Values of Precision, Recall, and F1-Score

Class_Type	Precision	Recall	F1-Score
Fresh apples	0.99	0.99	0.99
Fresh banana	1.00	1.00	1.00
Fresh oranges	0.99	0.97	0.98
Rotten apples	0.98	0.99	0.98
Rotten oranges	0.99	1.00	1.00
Rotten banana	0.97	0.98	0.98
Classification_Accuracy	0.99	0.99	0.99

In Table [4.2], we can understand the analysis of classification results by having the performance measures called Precision, Recall, Accuracy, and F1-Score. We have processed six classes Fresh apples, Fresh oranges, Fresh bananas, Rotten apples, Rotten bananas, and Rotten oranges and these results are noted in the table. Finally, the classification accuracy is about 99%.

4.8 Summary

In summary, we have developed an ensemble technique for identifying the freshness of the fruit. Our method incorporates the predicted characteristics of three pre-trained deep convolutional neural networks, each of which has a unique architecture (ResNet-50, VGG16, and DenseNet). Our ensemble model is validated using the research dataset, which contains both fresh and rotting examples of fruits across some categories. With an accuracy of 99.39%, our suggested ensemble model outperforms the existing Ensemble CNN [77]. In addition to adopting a majority vote classifier to determine the model's final performance, our method combined three models. Even more parameters are used in the training as discussed in the chapter. Therefore, our ensemble model suggestion aims to provide a better solution to the problem that my investigation brought to light.

Chapter 5

Results and Discussion

This chapter discusses the comparative analysis. The comparative result is validated using existing systems such as VGG [65], AlexNet [66], Dense Net [67], lightweight CNN [31], ResNet [24], lightweight ensemble [75], Ensemble CNN [76], Proposed Single CNN model, Ensemble CNN [77], and Proposed Ensemble CNN model. On the benchmark dataset of "fresh and rotten," the suggested ensemble approach is assessed using conventional performance criteria. The performance indicators are computed using the test image's actual class label and anticipated class label from the Fruits fresh and rotting dataset. The probability of accuracy is represented by the precision score, and the probability of completion is represented by the recall score. The harmonic mean of recall and precision is the F1 score. The model performs accurately, precisely, and completely, according to average performance measures. The accuracy, specificity, sensitivity, precision, recall, and F-score results evaluate the fresh and rotten fruit classification as well as food waste management. To execute with more samples CPU machines are not comfortable. So, in such cases, high-end configurations are required which means GPU machines may be required for implementation.

For example, if we run with fewer number samples in the dataset a greater number of layers may not be required to get the accuracy. But there is another problem if the input data is small that is the raining of the model may reflect the underfitting also. At the same time, there is a problem with overfitting. A "loss function" is typically used in deep learning with CNN to update the weight for subsequent training. The difference between the value predicted by the model and the actual value is what is referred to as the loss, which is a total of errors. As a result, the training loss and validation loss indicate the sum of mistakes using the respective training set and validation set. A low disparity between satisfactory training accuracy and test accuracy is a positive indication of a good generalization. As indicated previously, overfitting can therefore be noticed by observing the mismatch between the training loss and validation loss. This disparity reflects generalization abilities as well. These two results for each combination examined in this work would be possible. In addition to taking up too much room, the work's essential point could not be clear. As a result, the discussion will focus on the data augmentation technique's optimal outcome. So, we should be cautious about underfitting, and overfitting is given to building a new model from scratch.

5.1 Comparison of Proposed Single Model with existing approaches:

In reality, we used three pre-trained models using transfer learning for comparison, and those designs were tested using the dataset used in our study. The comparison of pre-trained models is discussed in Chapter 4 in detail about the working nature of each model. In this section, we are the results as mentioned below.

The proposed architecture differs from the existing approaches used for comparison [Section 5] in that the existing approach type of architecture was mainly pre-trained. In contrast, the former was built from beginning to end, meaning that the training pattern and data set determined the number of hidden layers and output layers. To address the problem statement, our model is subsequently suggested with a customized dataset.

The research was carried out using Anaconda Navigator and Jupiter Notebook, as mentioned in Chapter 2 in detail while discussing the proposed technique. Before starting the coding portion, significant Python libraries like TensorFlow and Keras were also included. Due to dealing with a sizable number of photos in the dataset, the system setup is also expanded simultaneously. The simulation parameters and hyperparameters are taken as mentioned in Chapter 3. The simulation results are mentioned here.

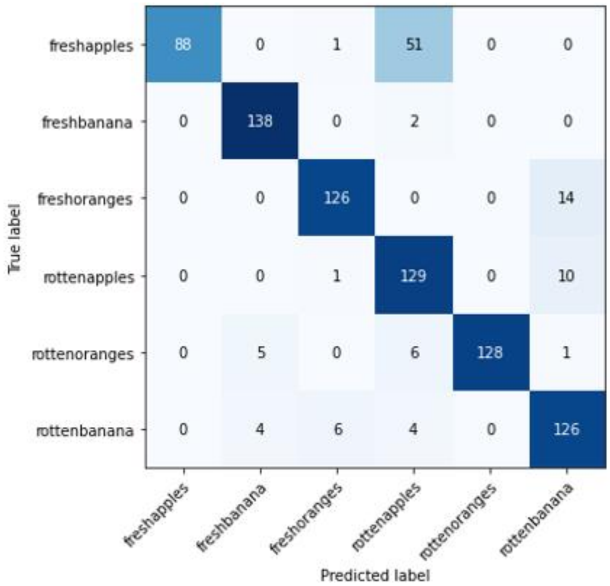

Figure 5.1 Confusion Matrix of Model (VGG16) [65]

In Figure 5.1, the confusion matrix of VGG16[65] reflects the simulation result applied to the dataset taken from our research work. The matrix displays the correct and incorrect predictions. Based on these values the performance measures are calculated and mentioned in the table [1].

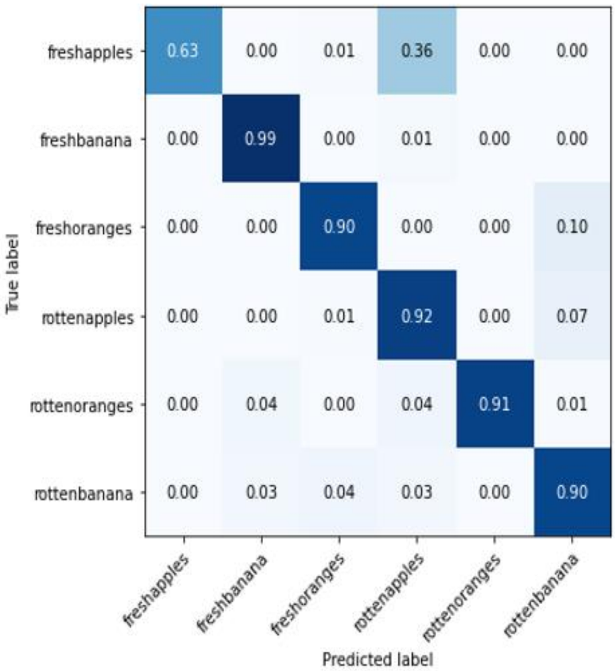

Figure 5.2 Confusion Matrix of Model (VGG16) [65]

In Figure 5.2, we can observe the correct and incorrect predictions percentage-wise. The researcher can understand easily which class is detecting correctly and which is not detecting properly to estimate the performance of the model taken for evaluation.

Table 5.1 Model (VGG16) Performance Measures

Class	Precision	Recall	F-Score
0	1	0.63	0.77
1	0.94	0.99	0.96
2	0.94	0.9	0.92
3	0.67	0.92	0.78
4	1	0.91	0.96
5	0.83	0.9	0.87
Total	0.90	0.88	0.88

In Table [5.1], all the performance metrics were mentioned to understand the model performance on our dataset. The precision, Recall, F1-Score, and accuracy are noted as 90%, 88%,88%, and 88% as mentioned.

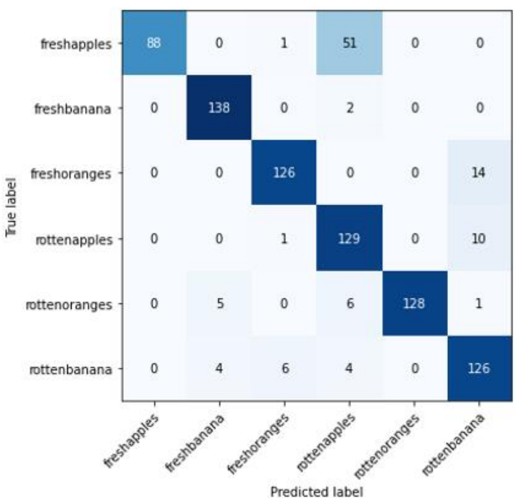

Figure 5.3 Confusion Matrix Class Wise for the Model AlexNet [66]

Figure 5.3 shows how the AlexNet [66] confusion matrix applied the model to the dataset from our research. The right and wrong predictions are shown in the matrix. The performance metrics are computed and listed in the table [5.2] based on these data.

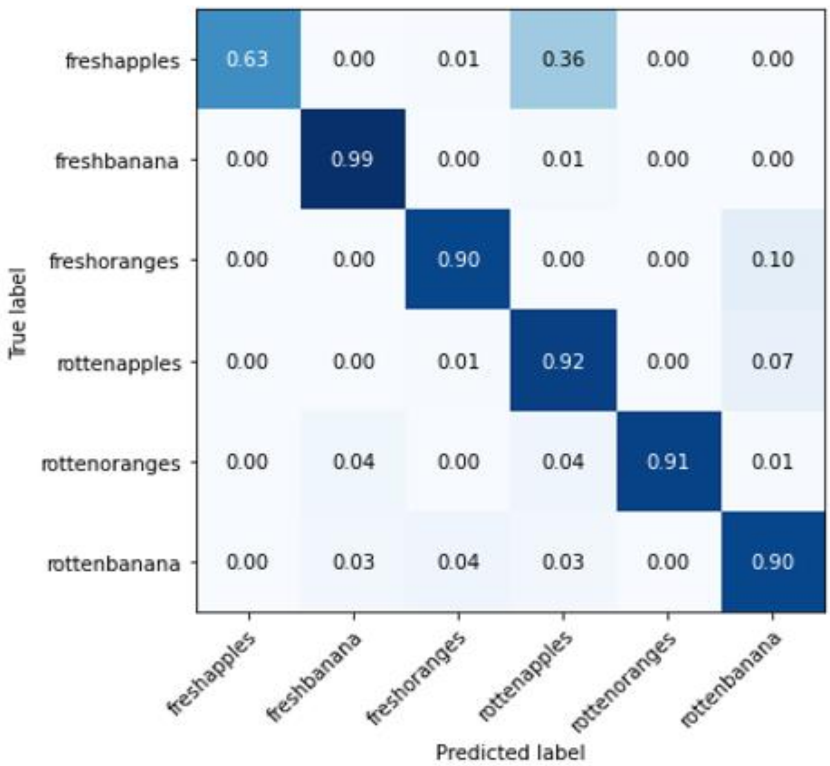

Figure 5.4 Confusion Matrix Percent Wise for the Model AlexNet [66]

Figure 5.4 shows the percentages of correct and wrong guesses. To estimate the performance of the model selected for evaluation, the researcher can quickly determine which class is correctly detecting and which is not.

Table5.2 Model (AlexNet) Performance Measures

Class	Precision	Recall	F-Score
0	1	0.63	0.77
1	0.90	0.99	0.96
2	0.94	0.9	0.92
3	0.67	0.92	0.78
4	1	0.91	0.96
5	0.79	0.9	0.87
Total	0.89	0.88	0.88

To analyze the model performance on our dataset, all the performance measures were listed in the table [5.2]. The noted values 89%, 88%, 88%, and 88% are recorded for precision, recall, F1-Score, and accuracy.

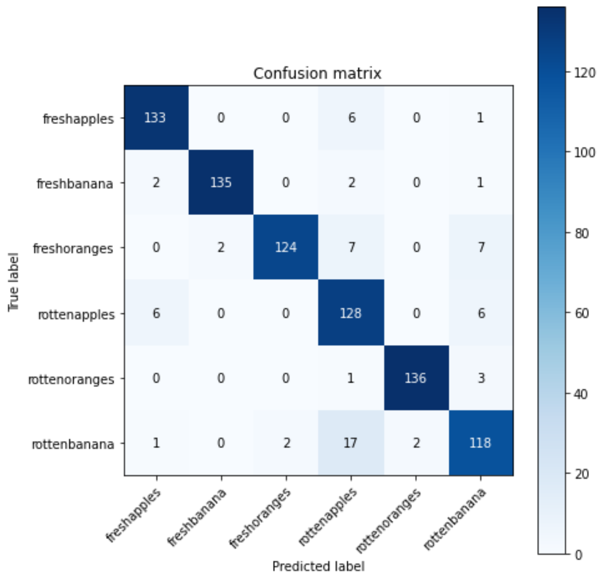

Figure 5.5 Confusion Matrix of Model (DenseNet) [67]

Figure 5.5 illustrates how the model was applied to the dataset from our study using the Dense Net [67] confusion matrix. The matrix displays both the correct and incorrect guesses. Based on these data, the performance metrics are calculated and shown in table [5.3].

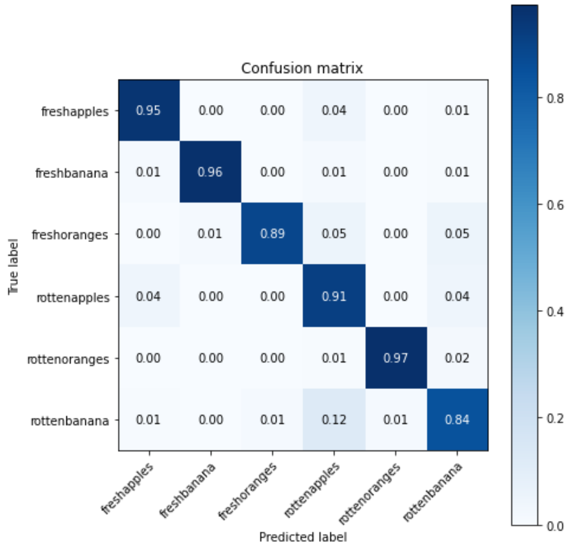

Figure 5.6 Confusion Matrix of Model (DenseNet) [67]

The percentages of accurate and incorrect responses are shown in Figure 6. The researcher can quickly determine which class the model chosen for evaluation is correctly identifying and which is not to estimate its performance.

Table 5.3 Model (DenseNet) Performance Measures

Class	Precision	Recall	F-Score
0	0.94	0.95	0.94
1	0.99	0.96	0.97
2	0.98	0.89	0.93
3	0.80	0.91	0.85
4	0.99	0.97	0.98
5	0.87	0.84	0.86
Total	0.93	0.92	0.92

All the performance measures were included in the table [5.3] for analysis of the model's performance on our dataset. The recorded precision, recall, F1-Score, and accuracy values are 93%, 92%, 92%, and 92%.

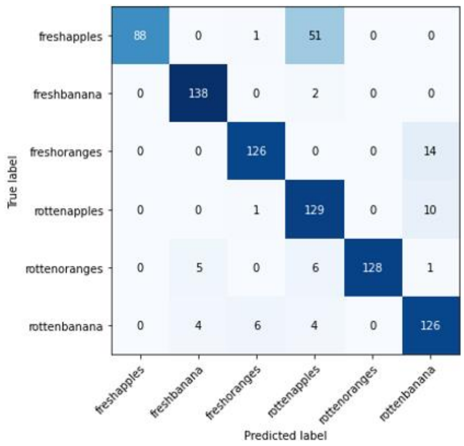

Figure 5.7 Confusion Matrix Class Wise for the Model lightweight CNN [31]

The lightweight CNN [31] confusion matrix was used to apply the model to the dataset from our investigation, as shown in Figure 5.7. The matrix shows both the correct and incorrect predictions. The performance metrics are computed and displayed in table [5.4] based on these data.

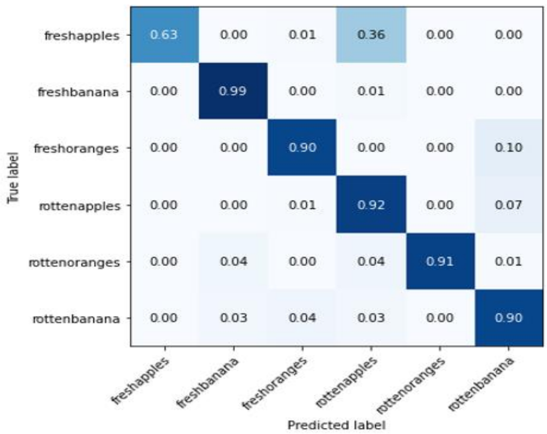

Figure 5.8 Confusion Matrix Percent Wise for the Model lightweight CNN [31]

Figure 5.8 displays the proportions of correct and erroneous responses. To estimate a model's performance, the researcher can easily establish which classes it correctly and incorrectly distinguishes.

Table 5.4 Model (lightweight CNN) Performance Measures

Class	Precision	Recall	F-Score
0	1	0.63	0.77
1	0.90	0.99	0.96
2	0.94	0.9	0.92
3	0.67	0.92	0.78
4	1	0.91	0.96
5	0.79	0.9	0.87
Total	0.89	0.88	0.88

Table [5.4] contains all the performance metrics for the model's evaluation on our dataset. The recorded values for accuracy, recall, F1-Score, and precision are 89%,88%, 88%, and 88%, respectively.

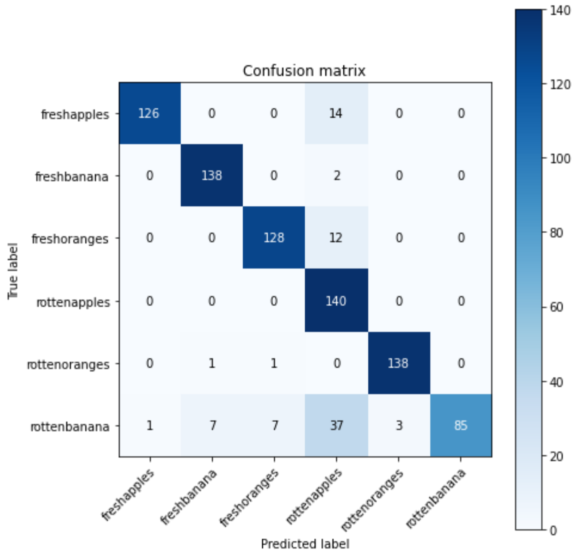

Figure 5.9 Confusion Matrix Class Wise for the Model CNN [24]

The model was applied to the dataset from our inquiry using the CNN [24] confusion matrix, as illustrated in Figure 5.9. Both the correct and incorrect predictions are displayed in the matrix. Based on these data, the performance metrics are calculated and shown in table [5.5].

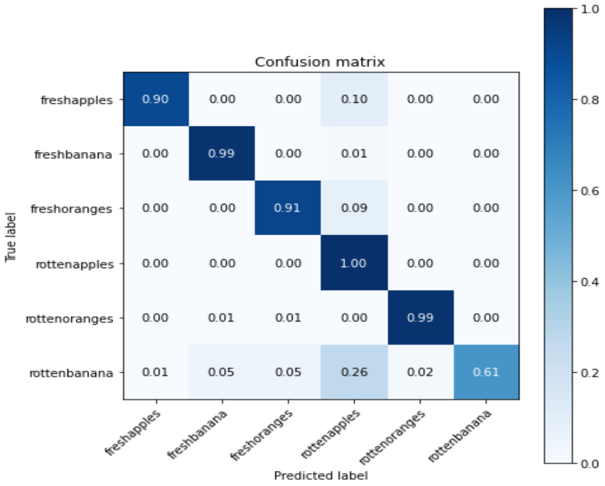

Figure 5.10 Confusion Matrix Percent Wise for the Model CNN [24]

The proportions of correct and incorrect responses are shown in Figure 5.10. The researcher can quickly determine which classes a model correctly and erroneously separates to measure its performance.

Table 5.5 Model (CNN) Performance Measures

Class	Precision	Recall	F-Score
0	0.99	0.90	0.94
1	0.95	0.99	0.97
2	0.94	0.91	0.93
3	0.68	1.00	0.81
4	0.98	0.99	0.98
5	1.00	0.61	0.76
Total	0.92	0.90	0.90

The performance metrics for the model's assessment on our dataset are all listed in Table [5.5]. Accuracy, recall, F1-Score, and precision recorded values are 92%, 90%, 90%, and 90%, respectively

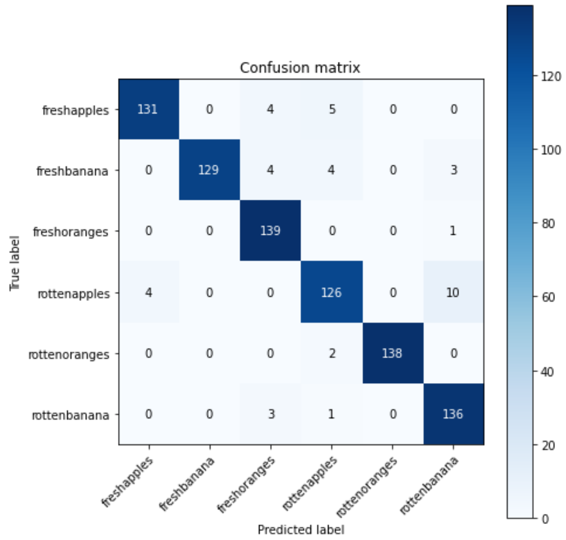

Figure 5.11 Confusion Matrix Class Wise for the Proposed Model [Chapter 3]

The proposed model [Chapter 3] confusion matrix was used to apply the model to the dataset from our investigation, as shown in Figure 5.11. In the matrix, both accurate and inaccurate forecasts are shown. The performance metrics are computed based on these data and displayed in table [5.6].

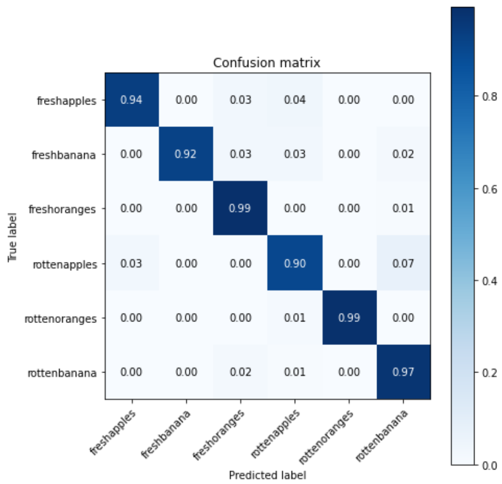

Figure 5.12 Confusion Matrix Percent Wise for the Proposed Model [Chapter 3]

Figure 5.12 displays the percentages of correct and incorrect responses. To evaluate a model's performance, the researcher can easily identify which classes it correctly and incorrectly divides.

Table 5.6 Model (Proposed Model) Performance Measures

Class	Precision	Recall	F-Score
0	0.97	0.94	0.95
1	1.00	0.92	0.96
2	0.93	0.99	0.96
3	0.91	0.90	0.91
4	1.00	0.99	0.99
5	0.91	0.97	0.94
Total	0.95	0.95	0.95

Table [5.6] has a complete list of the performance indicators used to evaluate the model on our dataset. The recorded values for precision, recall, F1-Score, and accuracy are 95%, 95%, 95%, and 95%, respectively.

Table 5.7 Results Comparison

Sno	Model	Accuracy
1	VGG [65]	88.4%
2	AlexNet [66]	87.9%
3	Dense Net [67]	91.8%
4	lightweight CNN [31]	87.6%
5	ResNetCNN [24]	90.2%
6	Proposed Single Model	95.14%

We can observe in Table 5.7 how different models give the result when running on the dataset taken for our research work. The major elements or parameters focused on are several convolutional layers of the pre-trained model to detect the test images of our data set. After the convolution operation, the pooling of layers can be done, and thereafter the filtered images will be supplied to the fully connected layers to identify the pattern in the input images. If more number layers are required to identify the images, then it leads to an increase in the number of hidden layers, at the same time number of neurons also will be increased and it will be difficult for computation with fewer configuration systems. We can see the performance of the proposed model when comparing it with the existing system1 in Figure 5.13

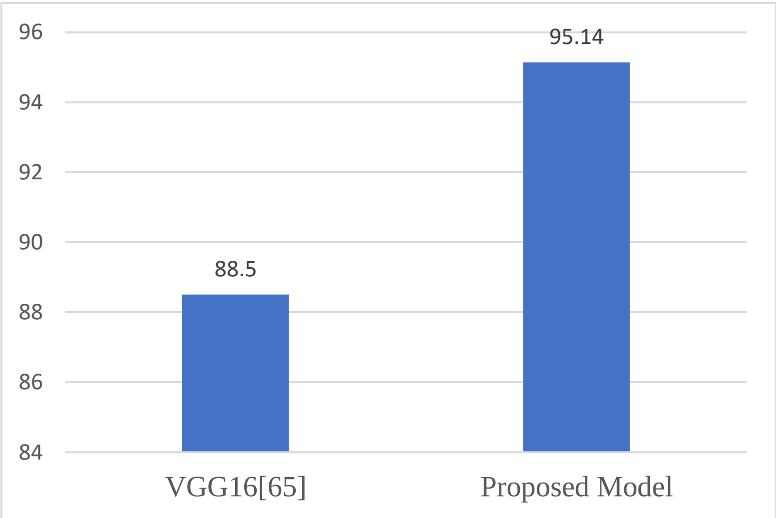

Figure 5.13 Proposed Model Comparison with Existing System [65]

In above figure 5.13, we have compared VGG16 with a proposed model and it supports a maximum of 19 layers. The number of filters used in this model is 3x3. At the same time, the pooling layer size is about 2x2.In this model, the input image size is 224x224. We got 88.5% accuracy when we executed the VGG16[65] on our data set. At the same time, the proposed model got 95.14% as mentioned already in Chapter 3.

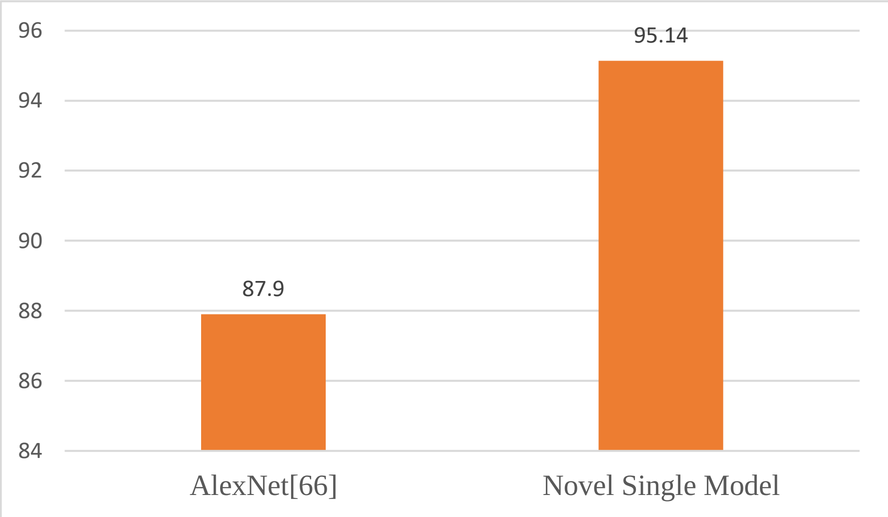

Figure 5.14 Proposed Model Comparison with Existing System [66]

About five convolutional layers and three dense layers make up this model. Max-pooling layers conceal the architecture in addition to these. The input image size for this design is around 224x224, and the ReLU activation function is utilized. We have got 87.9% accuracy on our dataset.

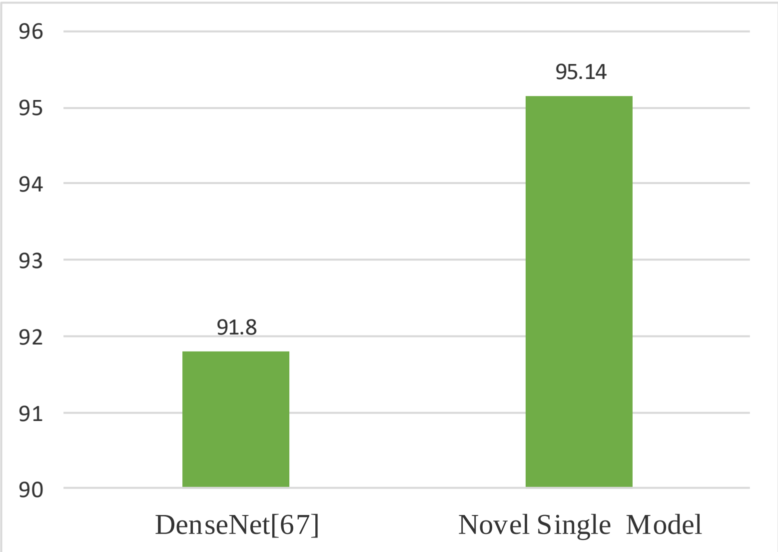

Figure 5.15 Proposed Model Comparison with Existing System [67]

Facebook proposed the term "Dense Net," also known as "Dense Convolutional Neural Network." By combining multiple layers, Dense Net connects them all directly. Both DenseNet-121 and DenseNet-169 take images with a resolution of 224x224 pixels. In Figure 5.15, we can understand the performance of the single proposed model when comparing it with the existing system.

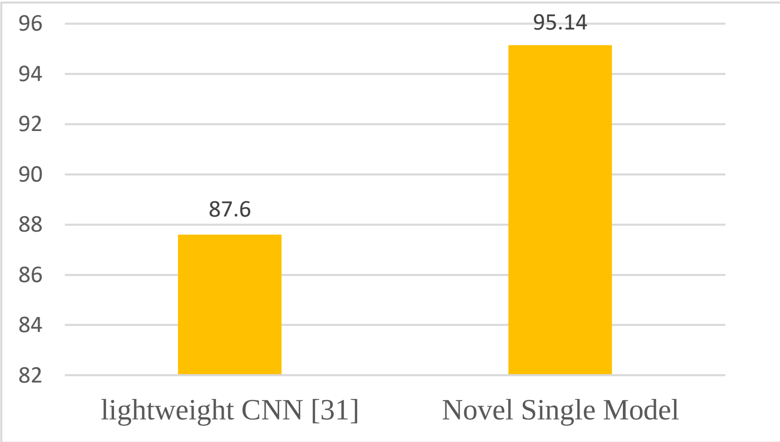

Figure 5.16 Proposed Model Comparison with Existing System [31]

The pre-trained deep learning model and six CNN light models are used to fine-tune the CNN model. In Figure 5.16, the model performance is displayed.

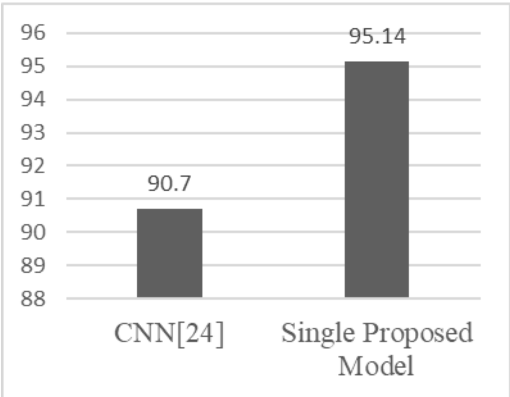

Figure 5.17 Proposed Model Comparison with Existing System [24]

To remove image noise, pre-processing was done on the image before classification. The real-time implementation was carried out using the Keras platform and NVIDIA Jetson Nano board based on the embedded system. 20 distinct fruits were divided into two different datasets, and while the experimental results were higher, the cost and complexity were higher. In Figure 5.17, we can observe the comparison as we discussed.

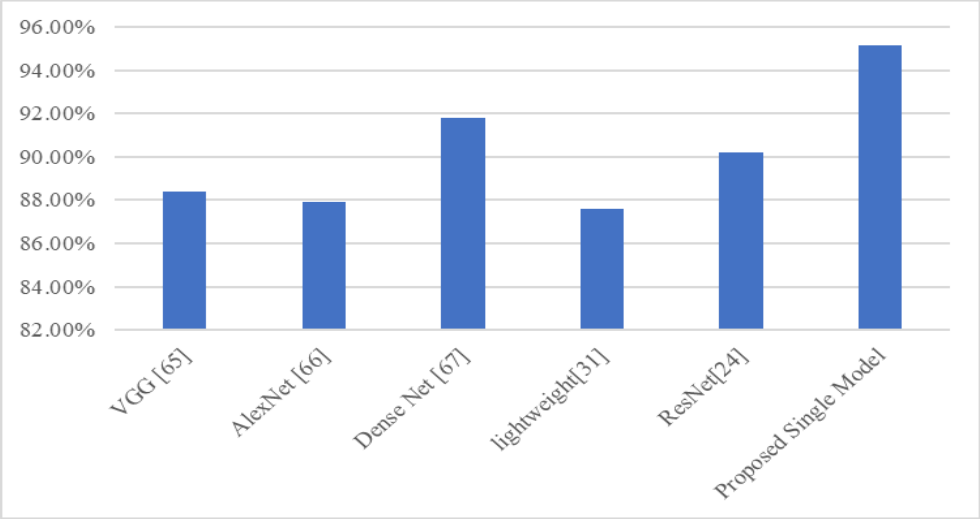

Figure 5.18 Proposed Model Comparison with Five Existing Systems [65][66][67][24][31].

5.2 PERFORMANCE MEASURES:

The performance metrics such as specificity, sensitivity, accuracy, precision, recall, and F-score measure to validate fresh and rotten fruit classification with its formulas are given below:

$$Accuracy = \frac{T_N + T_P}{F_N + T_N + F_P + T_P} \tag{1}$$

$$Precision = \frac{T_P}{F_P + T_P} \tag{2}$$

$$Recall = \frac{T_P}{F_N + T_P} \tag{3}$$

$$F - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Where the number of correctly predicted fresh fruits and the number of correctly predicted rotten fruits classes are true positive (T_P) and true negative (T_N). Moreover, the number of incorrectly predicted fresh fruits and the number of incorrectly predicted rotten fruits classes are true positive (F_P) and true negative (F_N).

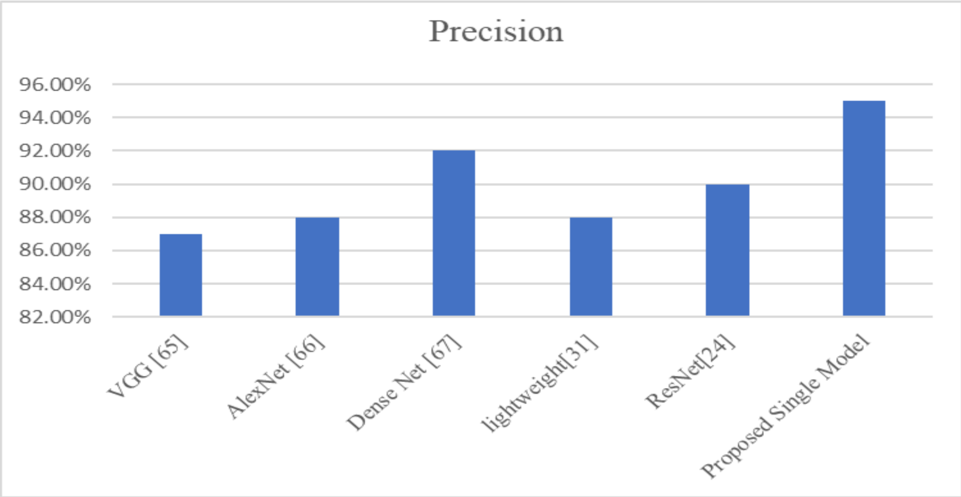

Figure 5.19 Precision Comparison of Models

VGG [65], AlexNet [66], Dense Net [67], lightweight CNN [31], CNN [24] and a single proposed model are state of art methods. Figure 5.19 illustrates the comparative analysis of precision. The precision of comparison models is 87%, 88%, 92%, 88%, 90%, and 95% obtained based on the state-of-art methods mentioned.

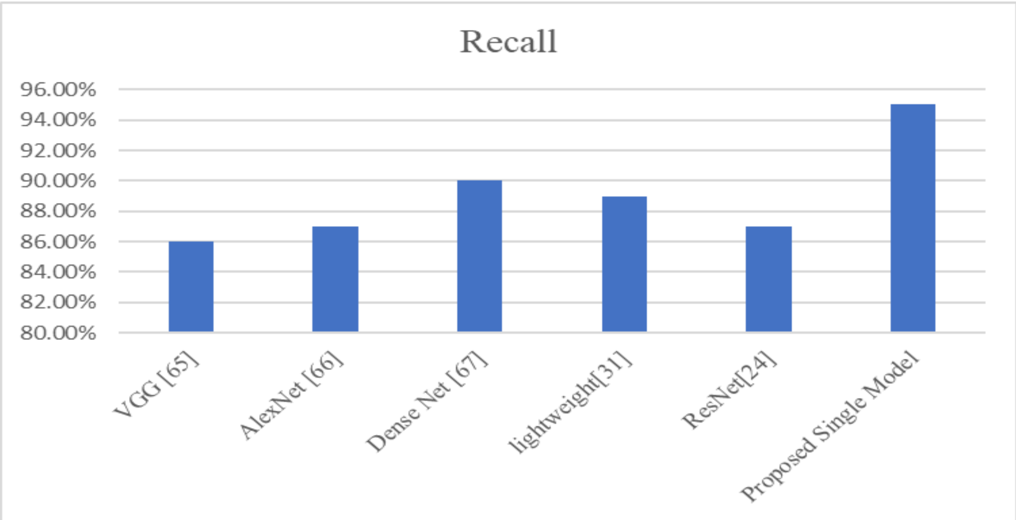

Figure 5. 20 Recall Comparison of Models

VGG [65], AlexNet [66], Dense Net [67], lightweight CNN [24], CNN [31] and a single proposed model are state of art methods. Figure 5.20 illustrates the comparative analysis of Recall. The Recall of comparison models is 86%, 87%, 90%, 89%, 87%, and 95% obtained based on the state-of-art methods mentioned.

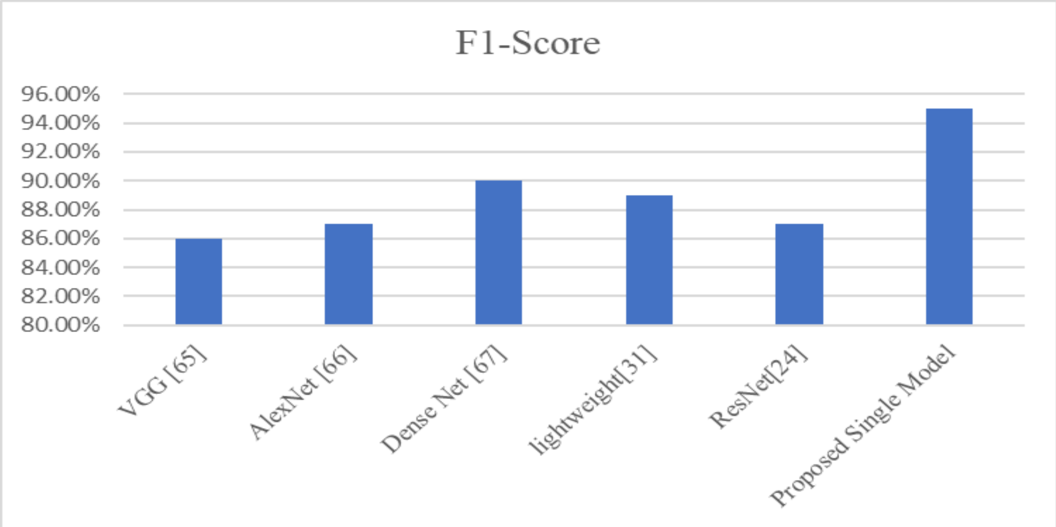

Figure 5.21 F-Score Comparison of Models

VGG [65], AlexNet [66], Dense Net [67], lightweight CNN [24], CNN [31] and a single proposed model are state of art methods. Figure 5.21 illustrates the comparative analysis of Recall. The Recall of comparison models is 86%, 87%, 90%, 89%, 87%, and 95% obtained based on the state-of-art methods mentioned.

5.3 Ensemble Proposed Model comparison with existing systems

The main goal is to educate and empower a team of classifiers. In both supervised and unsupervised learning scenarios, ensembles of learning machines combine their outputs, learning algorithms, or various views on the data in some way to provide more accurate and reliable predictions. This idea is only illustrated by the majority vote ensemble. The class that obtains the most votes is the one that the ensemble as a whole predicts. Sometimes the concept of the ensemble approach, may not be required to build the model for classifying the images from the dataset. Because we can also increase the number of layers in the single model itself. But if we want to complete the building of the model for a smaller number of samples always single models are recommended otherwise, we need to go for ensemble approaches as we may get the result of combined predictions from various models selected by the researcher. Finally, in our research work, we got, fortunately, the best result than the single model developed by us. In fact, in some cases, single models are not sufficient to resolve the issue of classifying the data and there will need to merge the predictions of one or more models to build the ensemble technique. From the literature, we can agree that ensembling is the combination of some selected models. In our case, we combined the models in different cases as already mentioned in Chapter 4. The proposed ensemble architecture differs from the existing approaches utilized in the comparison because, while the other approach architecture developed the ensembled one using only two models, our approach used three models for combination and additionally employed a majority voting classifier to determine the model's final performance. As stated in Chapter 4, there are other variations in the number of parameters. Thus, the goal of our ensemble model proposal is to offer an improved resolution to the issue highlighted by my study.

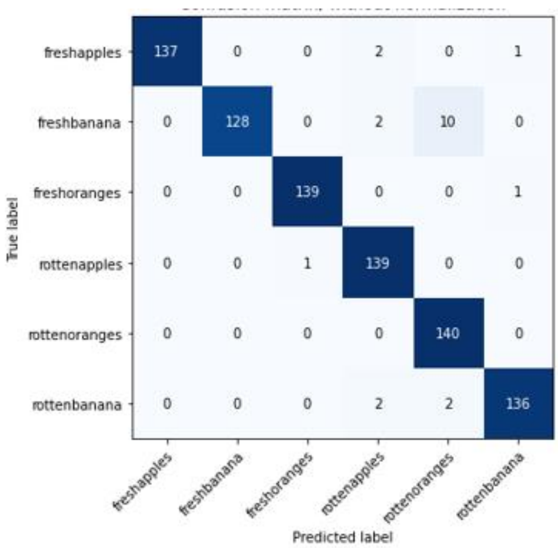

Figure 5.22 Confusion Matrix of Model CNN [75]

As seen in Figure 5.22, the model CNN [75] confusion matrix was applied to the dataset from our inquiry. Both correct and inaccurate predictions are displayed in the matrix. Based on these data, performance measures are calculated and shown in table [5.8].

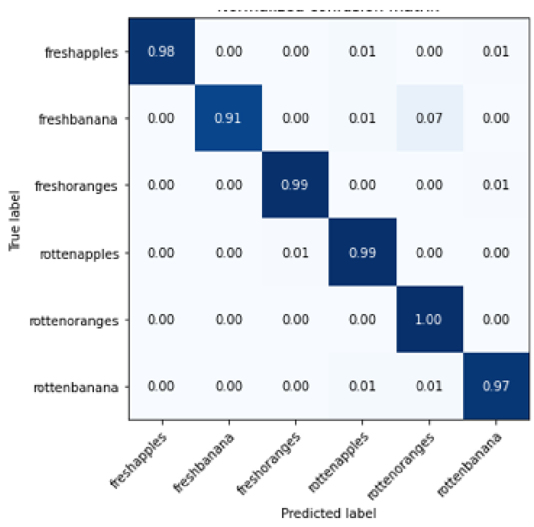

Figure 5.23 Confusion Matrix of Model CNN [75]

The percentages of accurate and incorrect responses are shown in Figure 5.23. The researcher can quickly determine which classes a model successfully and erroneously divides to assess its performance.

Table 5.8 Model CNN [75] Performance Measures

Class	Precision	Recall	F-Score
0	1.00	0.98	0.99
1	1.00	0.91	0.96
2	0.99	0.99	0.99
3	0.96	0.99	0.98
4	0.92	1.00	0.96
5	0.99	0.97	0.98
Total	0.98	0.97	0.97

The full list of performance measures used to assess the model on our dataset is provided in Table [5.9]. Precision, recall, F1-Score, and accuracy were measured at 98%, 97%, 97%, and 97%, respectively.

Table 5.9 Proposed Ensemble Model Result Comparison

Sno	Model	Accuracy
1	VGG [65]	88.4%
2	AlexNet [66]	87.9%
3	Dense Net [67]	91.8%
4	Novel Single Model	95.14%
5	Ensemble CNN [75]	96.2%
6	Light weight ensemble [76]	97%
7	Ensemble CNN [77]	97.8%
8	Proposed Ensemble Model	99.39%

All the models tested on the dataset are compared and displayed the accuracies in Table 5.9. We can understand the performance of multiple models to display and finalize the better model to detect and classify the fresh and damaged ones.

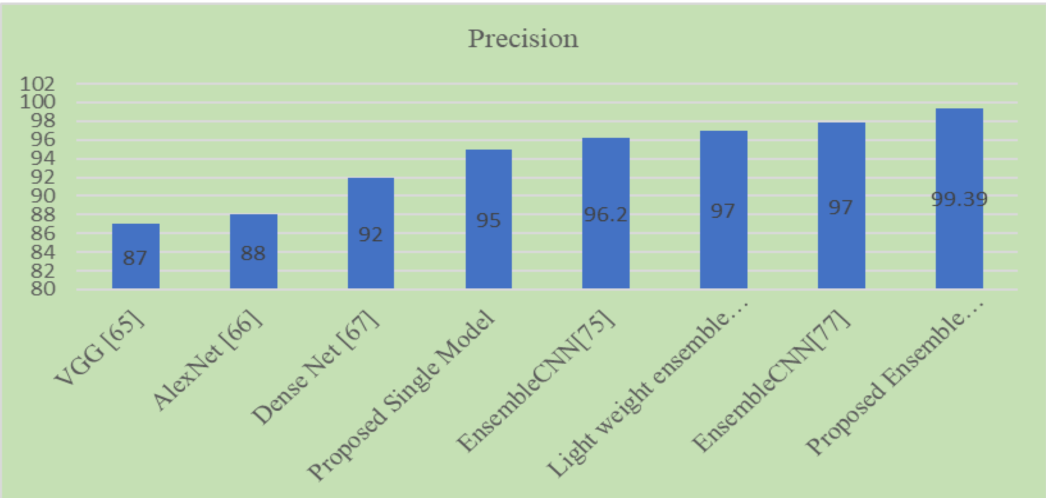

Figure 5.24 Precision Comparison

State-of-the-art techniques include VGG [65], AlexNet [66], Dense Net [67], Ensemble CNN [75], Lightweight ensemble [76], Ensemble CNN [77], and a single proposed model. The comparison of precision is shown in Figure 5.24 Utilizing the most recent techniques, the precision of the comparison models is 88%, 88%, 91%, 96%, 97%, 98%, and 95%.

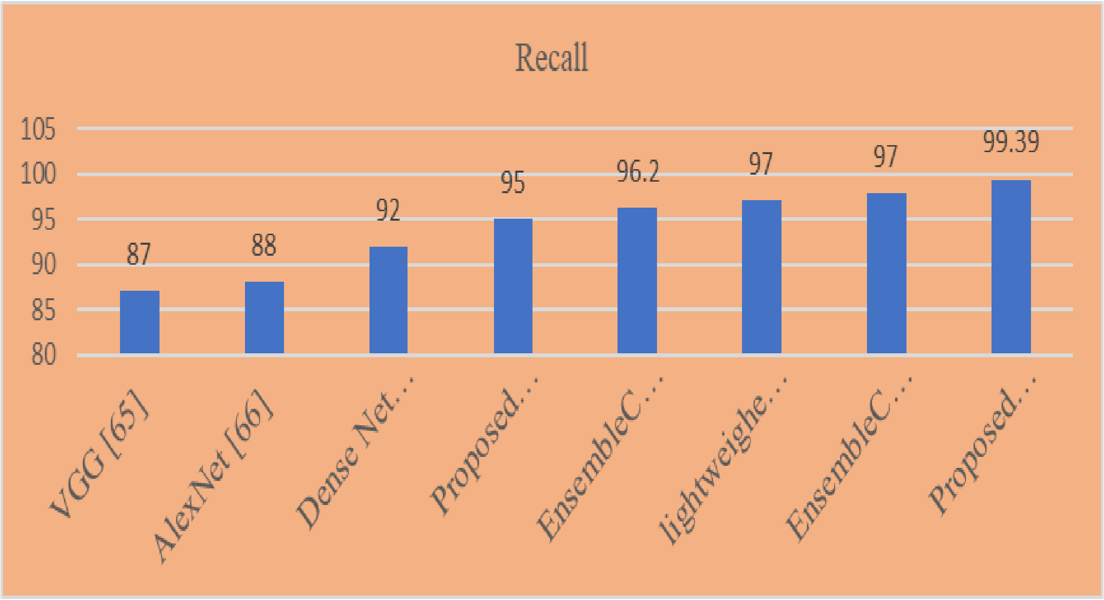

Figure 5.25 Recall Comparison

VGG [65], AlexNet [66], Dense Net [67], Ensemble CNN [75], Lightweight Ensemble [76], Ensemble CNN [77], and a single suggested model are examples of cutting-edge approaches. Figure 5.25 depicts the recall comparison. The comparison models' accuracy when using the most recent methods is 88%, 88%, 91%, 96%, 97%, 98%, and 95%.

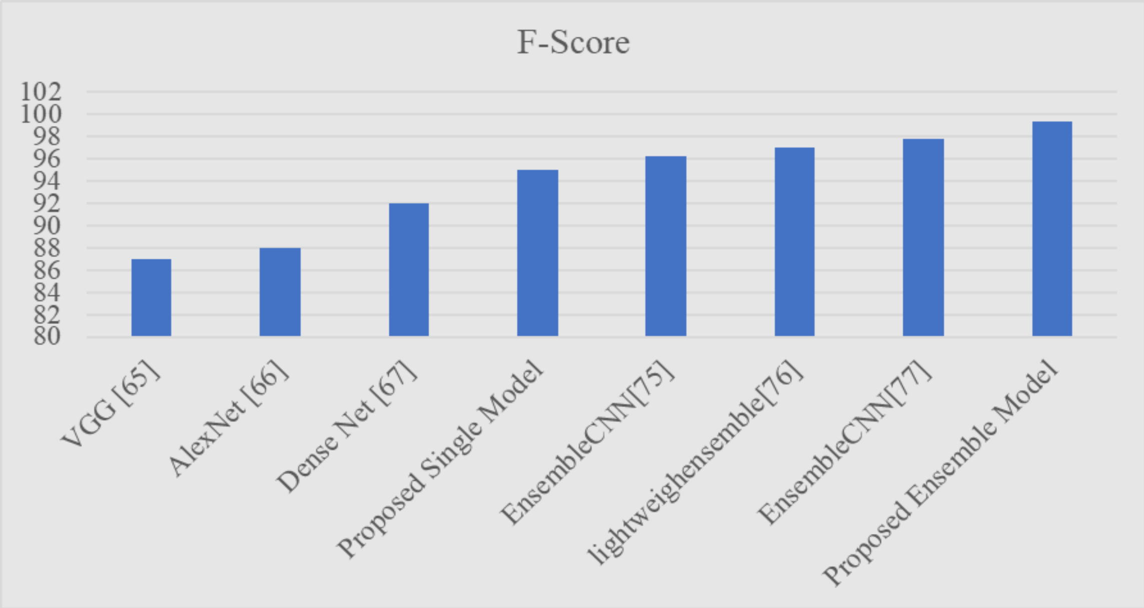

Figure 5.26 F-Score Comparison

Modern techniques include VGG [65], AlexNet [66], Dense Net [67], Ensemble CNN [75], lightweight ensemble [76], Ensemble CNN [77], and a single recommended model. In Figure 5.26, the recall comparison is shown. Utilizing the most modern techniques, the accuracy of the comparative models is 88%, 88%, 91%, 96%, 97%, 98%, and 95%.

The suggested ensemble model performs better on several metrics, including accuracy, recall, and F1-Score, than the previous methods employed in the comparison. We have processed six classes in the suggested model in addition to these measures. In the end, there is a 99% categorization accuracy. The confusion matrix predicted the misclassified samples in each class. The most recent methods include a single suggested model, VGG [65], AlexNet [66], Dense Net [67], Ensemble CNN [75], Lightweight ensemble [76], and Ensemble CNN [77]. As a result, we can now clearly understand our model's efficiency due to this study.

5.4 Summary:

We have executed all the above-mentioned architectures with our dataset and noted the results. Before running those models on our dataset, we arranged the dataset properly by applying the augmentation technique, resizing images, and labeling. In our Proposed Single Model, we can observe the model's goodness in detecting and classifying fresh and damaged fruits with 95.14% Accuracy. For traying, almost we took 7560 images from the dataset after applying the augmentation, for every iteration, the total number of trainable images is divided by batch size and calculated accordingly. Due to this, we have increased our system configuration otherwise time duration will be increased for each iteration, and in turn, overall model building time also would be increased. Actually, for finalizing the model we took a lot of time because already we had a target accuracy percentage in terms of existing approaches, so we spent much time on this to conclude attaining at least better accuracy. The results of the experiment demonstrated that the proposed ensemble approach delivered cutting-edge outcomes for classifying both fresh and damaged fruit. The robustness and recognition rate have both improved over the prior study. The outcomes of our study demonstrate that, when it comes to categorizing fruit freshness, our suggested ensemble method outperforms both the other single model and the existing approaches by 99.39%.

Chapter 6

Conclusion and Future Scope

This chapter will discuss the conclusion of the complete research work and its future directions.

6.1 Conclusion

The entire research is focused on detecting and classifying excellent and damaged fruit to reduce food waste. In our study, we developed two models, single and ensemble, which are more helpful in recognizing the damaged fruit accurately than existing models. Firstly, in the case of a single model, the outcomes show that the proposed CNN model outperforms current techniques in accurately distinguishing between fresh and rotting fruits. As a result, the suggested CNN model will automate the ability of the human brain to differentiate between new and rotting fruits, decreasing the possibility of human errors in fruit classification. The proposed CNN model provides an accuracy of 95.14 percent. Secondly, this study suggests an ensemble technique for identifying fresh and rotten fruit with a 99.39% accuracy rate. The proposed method individually trained three different DCNN models to boost the recognition rate before combining their outputs.

The experiment results demonstrated that the proposed ensemble approach delivered cutting-edge outcomes for classifying fresh and damaged fruit. The robustness and recognition rate have both improved over the prior study. The results of our study demonstrate that, when it comes to categorizing fresh fruit, our suggested ensemble method outperforms than existing and single model. These results showed that our proposed method is suitable for assessing the fruit's quality. To reduce overall food waste, it is necessary to construct another reliable architecture that can identify and classify both damaged and fresh food products.

Our present literature led us to conclude that most food waste occurs in households, with the rest of it coming from retail, shopping, exporting, importing, purchasing, and other reasons. When food is wasted in the home, it's usually due to a few factors: overcooking, wasting food on plates, lack of smart refrigerators, unplanned buying, and expiry dates on stored items.

The proposed model is best suited for controlling the wastage in households and supermarkets and in other areas to classify the fresh and damaged fruit where fruits are used one by one. However, the model can also detect fresh or damaged fruit when used group-wise to the maximum extent.

With the help of various statistics from reputable organizations, chapter one provides information on global food waste. Similarly, the chapter also provides a general concept of the environmental problems caused by unanticipated garbage from various sources for the reasons described.

To prevent food waste, chapter 2 gives insight into the many methods authors have used to distinguish between fresh fruit and fruit that has been damaged. This study's problem has been the subject of a literature review conducted over a few months using a variety of papers and articles that have been considered. This chapter effectively and efficiently explains the findings of several studies that employed various techniques for distinguishing between fresh and spoiled fruit or food. The researchers found a few gaps and worked to fill them with their findings. The works of several researchers that were taken into consideration for this thesis work are explained below.

Chapter 3 discusses the suggested method for identifying and categorizing fresh and rotting fruit to prevent food waste. Convolutional Neural Network (CNN), a deep learning method that is an outstanding method or approach for classifying images, is used in the suggested model. The data set was considered from the Kaggle website, and preprocessing techniques were also utilized to clarify identification and classification. The performance evaluation was conducted based on variables like classification accuracy, Precision, Recall, and F-Score. It is compared against a few already-in-use systems to demonstrate the model's performance.

The methodology of an ensemble model to identify and categorize fresh and damaged fruit is covered in Chapter 4. To determine which is superior, it is necessary to compare an ensemble model against a single model in the same situation. The proposed ensemble model is constructed with some pre-trained models' help. To demonstrate the effectiveness of our approach in identifying and categorizing the model, the proposed ensemble models are also contrasted with a few other existing models. Tuning parameters, data collection, and other technical assistance are used as needed to develop our model. All of these specifics are covered in the chapter.

In chapter 6, the comparative analysis is covered. Using already-in-use systems such as VGG [65], AlexNet [66], Dense Net [67], Ensemble CNN [75], lightweight ensemble [76], Ensemble CNN [77], Proposed CNN, and Proposed ensemble CNN model, the comparative result is proven. Using standard performance metrics, the proposed ensemble technique is evaluated on the benchmark “fresh and rotting” dataset. The test image's actual and anticipated class labels from the Fruits fresh and rotting datasets are used to calculate the performance metrics. The precision score reflects the likelihood of accuracy, whereas the recall score reflects the likelihood of completion. The F1 score is the harmonic mean of recall and precision. According to average performance measures, the model executes accurately. Chapter 6 discusses the conclusion of the complete research work and its future directions.

6.2 Future Scope

The main agenda of the globe is to provide food for people who are in need and also to control the food waste that happens because of various reasons discussed in the literature. The risk of overproduction may be reduced by farmer collaboration. Farmers are helped to discover solutions to the problem of agricultural shortages by transferring surplus crops from one farm to another. Poor farmers may occasionally harvest their crops early when there is a food shortage in the middle of the growing season.

- Early harvesting can occasionally result in food loss for both developing countries and some wealthy countries.
- Before making a food purchase, we should inspect our pantry, freezer, and refrigerator to save money. We base our meal planning on a weekly assessment of what needs to be consumed.
- Users should prepare their meals for the upcoming week before shopping and only buy what they need.

- Make a grocery list based on how many meals the user intends to consume at home. Consider how often they'll eat out, whether they'll use frozen prepared meals, and whether any of our meals will have leftovers.
- Expanding this study's scope to include more expansive categorized fruits and vegetables will increase the likelihood of minimizing food waste, a significant issue in modern society.
- Future research also suggested boosting the number of foods like vegetables, grains, and other products in the new and damaged categories.
- Subsequent studies recommended applying the approach by including different fruits, vegetables, and other dietary items. To prevent food waste, more data samples need to be added to establish a reliable system for classifying fresh and damaged food items using deep learning techniques and involve the LSTM network with Natural Language Processing (NLP) for text generation where required in the model.
- The possibility that researchers would be inspired to study this field would rise. As a result, they were ultimately assisting our country in achieving SDG 12.3 of the UN.

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