AN INTELLIGENT SYSTEM TO DETECT LIVER CANCER USING DEEP CONVOLUTIONAL NEURAL NETWORK

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In

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2024

<u>DECLARATION</u>

I, hereby declare that the presented work in the thesis entitled “An Intelligent System to Detect Liver Cancer using Deep Convolutional Neural Network” in fulfilment of degree of **Doctor of Philosophy (Ph.D.)** is outcome of research work carried out by me under the supervision of Dr. Shailendra Kumar Singh, working as Assistant Professor, in the Department of Computer Science and Engineering of Lovely Professional University, Punjab, India and co supervision of Dr. Moin Hasan, working as Assistant Professor, in the Department of Computer Science and Engineering of Jain deemed-to-be University, Bengaluru, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. 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 Intelligent System to Detect Liver Cancer Using Deep Convolutional Neural Network” submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the Department of Computer Science and Engineering, is a research work carried out by Mohd Anwarul Siddique, 4200323, is bonafide record of his 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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ABSTRACT

Liver is the greatest and largest glandular organ in human body by weight. It is absolutely fundamental to human life as it performs some vital functions such as digestion, metabolism and filtering of possibly harmful bio-chemicals from blood. Due to changing lifestyle and excess consumption of packaged food, liver diseases such as liver cancer are becoming very common. According to a survey conducted by Globocon 2020, Liver Cancer was the sixth biggest reason of death globally due to deaths caused by cancer. Survival rate in liver cancer is found to be extremely low because of the complexities in early diagnosis, hasty progression, and limited availability of targeted drugs. Like any other serious disease, successful treatment of liver cancer also requires an early and accurate diagnosis.

Liver cancer is broadly categorized as primary and secondary liver cancer. Primary liver cancer, such as Hepatocellular carcinoma (HCC), Angiosarcoma, Intrahepatic Cholangiocarcinoma, Hemangiosarcoma, and Hepatoblastoma,is caused due to liver cells. HCC is observed to be the most common liver cancer, generally caused due to hepatitis A/B. On the other hand, secondary liver cancer although appears in liver but actually caused due to the cells of external organs such as colon, stomach, breast, pancreas, or Livers, etc. Collectively, liver cancer may be caused due to hepatitis, diabetes, alcohol consumption, aflatoxin’s exposure, inherited liver diseases or fatty liver acid, etc. Major symptoms of liver cancer include vomiting, nausea, loss of appetite, loss of weight, fatigue, upper abdominal ache, abdominal swelling, or jaundice, etc.

Liver cancer is generally diagnosed in males and aged people. Clinically, liver cancer is diagnosed by analyzing the level of alpha-fetoprotein and bilirubin enzymes in blood, along with liver biopsy. In the last decade various manual tests have been adopted to diagnose the liver cancer such as immunotherapy, Oncolytic Virus Therapy, and Cytotoxic Chemotherapy.

A survey by world health organization (WHO) concluded that early detection of liver cancer increases survival rate of persons suffering from cancer. However, diversity in morphology, risk factors, micro-environmental discrepancies, and genetic susceptibilities always pose a huge challenge in early detection of liver cancer.

Traditionally, cancer detection is done by conducting a series of medical examinations on patients such as liver biopsy, blood test, bilirubin test and many more. These methods are time consuming, slow and their accuracy depends on the quality of lab and expertise of medical examiner. Due to these limitations traditional methods are slow and inaccurate.

Recently computer aided diagnosis of liver cancer has shown promising results in early detection and treatment of liver tumor. Many imaging techniques such as magnetic resonance imaging (MRI), positron emission tomography (PET) are used to detect liver cancer, with Computed Tomography (CT) images being the most widely used technique. Computer Aided Diagnosis (CAD) involves studying CT scan images to detect liver cancer. Visually cancer is the abnormal pattern with undefined structure that can be found in liver Computed Tomography (CT) images.

CAD is a two-step process, in first step the CT images are preprocessed and segmented to obtain region of interest(ROI). In the next step a classifier is used to predict whether the cancer cell is present in the segmented image or not. Many different algorithms and techniques have been suggested by various authors for segmentation and classification of liver cancer. Earlier several machine learning algorithms such as support vector machine, random forest etc. were used for cancer detection. These algorithms suffer from the drawback of improper training data and their accuracy varies significantly for noisy data. Also it was a big challenge to define features and select proper feature extraction techniques for cancer detection. Further it was observed that such algorithms were suitable for binary classification only. They have low accuracy for multiclass cancer detection.

This research proposes a solution to all above problems by designing three novel techniques to preprocess, segment and classify the medical images into multiclass liver cancer detection.CT images are usually DIACOM images which are converted into jpg or png images before being used for cancer detection. Also, original DIACOM images are of high resolution and colored. These images are converted into gray scale images and their size is also reduced to 512*512 or 256*256. These changes can result in information loss from original images. Also, it may happen that due to some technical or human errors there might be noises present in medical images. Therefore, it becomes very important to pre-process input images to remove noises in order to achieve better efficiency from cancer detection algorithms. It is therefore important to pre-process CT images before being used as input for cancer detection algorithms. This research presents a robust technique for pre-processing CT images to remove any possible noise present in CT images. This technique involves use of double stage Gaussian filtering in order to smooth out the edges, which helps in separating multiple objects from each other and clearly identifying the boundaries of each object. Median filter is used to remove salt and pepper noise, Contrast Limited Adaptive Histogram (CLAH) is used to enhance the contrast of image. The images obtained from double stage Gaussian filtering, median filtering and CLAH filtering are combined using image fusion technique in order to obtain final pre-processed image. The evaluation metrics used for this technique are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Metrics (SSIM). Results obtained are SSIM is .85, PSNR is 57.56 dB, and MSE is 0.13.

In computer vision-based biomedical image analysis, liver segmentation is a critical step in detecting liver cancer. Due to the complicated structure of abdominal computed tomography (CT) images, noise, and textural differences across the image, liver segmentation is a key task that results in avoiding under-segmentation and over-segmentation.Segmentation is a very challenging task. Segmentation algorithms suffer from over segmentation (including other parts in liver area) and under segmentation (leaving some portion of liver area in segmented image). This research proposes an effective method for segmentation. It uses marker-controlled watershed algorithm for segmenting liver CT images. Watershed algorithm converts the black and white CT scan images into a surface having hills and valleys[9]. Bright intensity pixels represent hills and dark intensity pixels represent valleys. Hills are punctured from the top and water is poured from the top. Dam boundaries are created to prevent mixing water from different regions. Valleys are filled first and then the hills. When water is filled completely, different regions are given different colors. These colored regions are then separated as different objects. Obtained values of evaluation parameters are DS= 0.968, VOE=0.326, JI=0.937 and RVD=0.09.

Final step includes feature extraction and classification. Feature extraction helps to collect the distinctive characteristics of the liver image to distinguish between the normal and cancerous liver image. Important features of liver tumor include its shape, size, color, volume, and density, etc. In classification, the detected liver cancer is classified into the various categories as already discussed above. Feature extraction and classification can be combined in one step or can be carried out separately. Deep learning techniques combine the feature extraction and classification process. In fact it is the ability of deep learning techniques to extract some features that are not yet identified by medical experts. However, deep learning algorithms require huge amount of input data and large training time. But once the system is trained it provides high classification accuracy and fast output. This research proposes a classification technique based on Deep Convolutional Neural Network. Proposed Model has achieved high classification accuracy of 99.2%.

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LIST OF ABBREVIATIONS

HCC	Hepatocellular Carcinoma
PACS	Picture Archiving and Communication Systems
EHR	Electronic Health Record
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
PET	Positron Emission Tomography
CNN	Convolutional Neural Networks
ROI	Region of Interest
AUC	Area Under the Curve
DTCWT	Double Tree Complex Wavelet Change
UDWT	Undecimated Wavelet Change
DAN	Deep Adversarial Networks
WLF	Weighted Loss Function
ReLU	Rectified Linear Unit
DGF	Double Gaussian Filter
CLAHE	Contrast Limited Adaptive Histogram Equalization
MSE	Mean Squared Error
PSNR	Peak Signal-to-Noise Ratio
SSIM	Structural Similarity Index
UIQI	Universal Image Quality Index
DS	Dice Similarity
VOE	Volumetric Overlap Error
JI	Jaccard Index
RVD	Relative Volume Difference

Chapter 1

INTRODUCTION

The liver is largest organ in abdominal area of human body, placed on the lower right side of stomach[1]. Its main task is to filter blood that comes in from the digestive tract prior to sending it to the rest of the body. It aids in chemical and drug detoxificationandmetabolism[2]. The liver essentially produces some proteins that aid in blood coagulation [3]. Primary and secondary are the two types of liver cancer[4]. Primary liver cancer is triggered by anomalies within the liver[5]. Hepatocellular carcinoma (HCC), intraheptic cholangiocarcinoma andhemangiosarcomaare the several types of primary liver malignancies [6]. HCC is the most common type of liver cancer, accounting for 75% of all cases[7]. Over 800,000 people die each year from liver cancer[8], making liver cancer fourth most cause of death, according to the world health organization (WHO). Since liver cancer frequently manifests with few symptoms in its early stages and results in late diagnosis and few treatment choices, early identification is essential for effective therapy and improved patient outcomes[9]. Researchers and healthcare professionals are using artificial intelligence (AI) and sophisticated medical image analysis techniques to build intelligent systems that can help in the early diagnosis of liver cancer in an effort to solve this urgent healthcare concern[10].

1.1 Background Study

This section first explores the various types of liver cancer along with their probable causes. Further, it also explains liver cancer detection process in detail. This chapter also provides statics regarding the growth rate of liver cancer, total number of liver cancer cases, and distribution of cancer cases among males and females and survival rates of various types of cancer.

1.1.1Types of Liver Cancer

Depending upon the place of origin, liver cancer can be broadly categorized as primary and secondary liver cancer. In Primary liver cancer, the tumor originates inside liver[11]. Common symptoms are weakness and tiredness, abdominal ache, loss in desire for food, yellowing of skin, impenetrable weight loss, and eyes, and dark urine, etc.[12]. It is generally caused due to hepatitis b or hepatitis-C, fatty liver disease – often related to elevated carbohydrate diet, obesity, excessive alcohol consumption, and genetic disorders. Primary liver cancer is further classified as

- Hepatocellular carcinoma (HCC): HCC is major king of primary liver cancer and it accounts for almost 75% of all the primary liver cancers[13]. The chief cause of HCC is hepatitis B or Hepatitis C. HCC is also called as hepatoma as it originates it the hepatocytes which is the liver's main cell type[14].
- Intrahepatic Cholangiocarcinoma: It initiates in bile duct that connects gall bladder to liver. It is often referred as cholangiocarcinoma. It shows some common symptoms such as extremely itchy skin, yellow skin and eyes, and white stool[14].
- Angiosarcoma: It is also a atypical kind of primary liver cancer that originates in the blood vessels. Angiosarcomas make up about 1% to 2% of all sarcomas. They are most common in people over the age of 70 years[15].
- Hepatoblastoma: It is a form of liver cancer that affects only young children (usually prematurely born children) and is also very rare. Most cases appear during the first 18 months of life[16].

On the other hand, in secondary liver cancer, tumor originates in some other organ (like colon, stomach, breast, pancreas, or Livers) and spreads in the liver later on. Major causes of secondary liver cancer are diabetes, alcohol consumption, aflatoxin’s exposure, inherited liver diseases, and fatty liver acid, etc[17]. In some cases infection due to hepatitis B or hepatitis C may also cause secondary/metastatic liver cancer. Fig. 1.1 shows a categorical view of liver cancer.

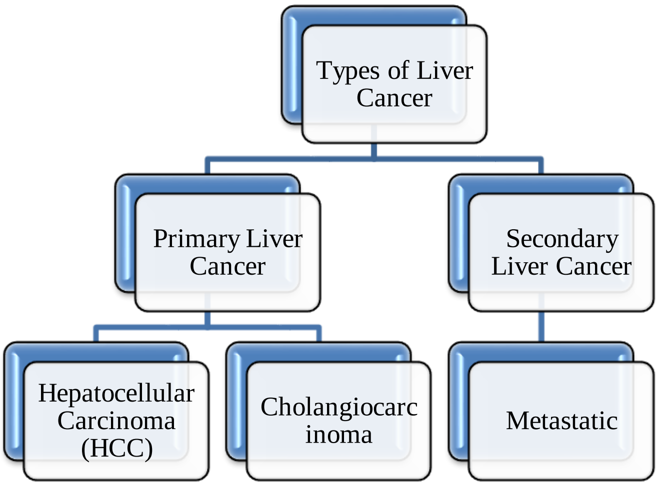


Fig. 1.1 Types of Liver Cancer[18]

1.1.2 Liver Cancer Detection Methods

Clinically, to detect liver cancer certain test is conducted such asconducting medical tests to analyze the level of alpha-fetoprotein enzymes in blood, and biopsy. Recently, various manual tests were also used to analyze the liver cancer such as oncolytic virus therapy andimmunotherapy[19]. With the advancement in technology, many new approaches are being used for liver cancer detection. One such approach is genetic approach in which genes are studied to identify liver cancer and probability of liver cancer in future. Some data mining algorithms are also utilized to forecast the possibilities of whether a person can have liver cancer in future or not. These algorithms use historical data to create models that can foretell the possibility of liver cancer. Recently, medical image processing has also gained popularity for liver cancer detection. For better understanding, Table 1.1 gives a comparison of most popular approaches for liver cancer detection.

Table 1.1 Various Approaches to Early Cancer Detection

Computer aided Genetical Approach	Data Mining/Machine Learning	Deep learning using medical images
Aims to find genes	Aims to find risk factors	Aims to detect cancer from medical images
Works on micro array data	Works on historical data	Works on medical image processing
Results in terms of differential genes	Results in terms of possibilityof liver cancer in future	Results in accurate findings.
Problem comes in identification genes	Problem comes in predicting risk factors.	Problem comes during segmentation of an image.
Utilizes statistical methods	Uses Data Mining Techniques	Uses image processing Techniques

1.1.3 Liver Cancer Related Statics

Liver is the largest organ present in top right corner of the stomach. Its shape and size varies for male and female and for different age group persons. The structure of liver is shown in Fig. 1.2 below. Due to changing life styles, liver related diseases, especially liver cancer are increasing at a rapid pace.

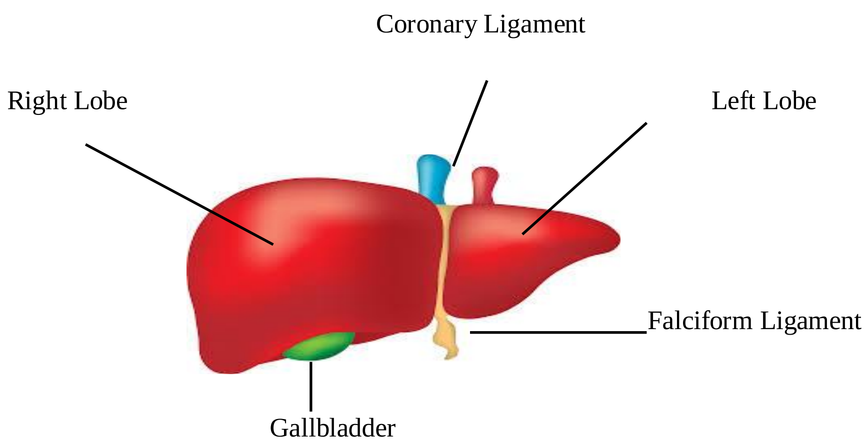


Fig. 1.2 Structure of Human Liver[1]

Since liver is a very important organ, as it performs a very important function of blood purification, liver cancer has a very low survival rate. Survival rate of cancers are calculated by a metrics called 5 year survival rate[20]. It is a measure of the rate, that from the date of detection of cancer, how many patients were able to survive for 5 years. Fig. 1.3 below presents the 5 and 10 year survival rates of various types of cancer. This research was conducted by world health organization in 2020.

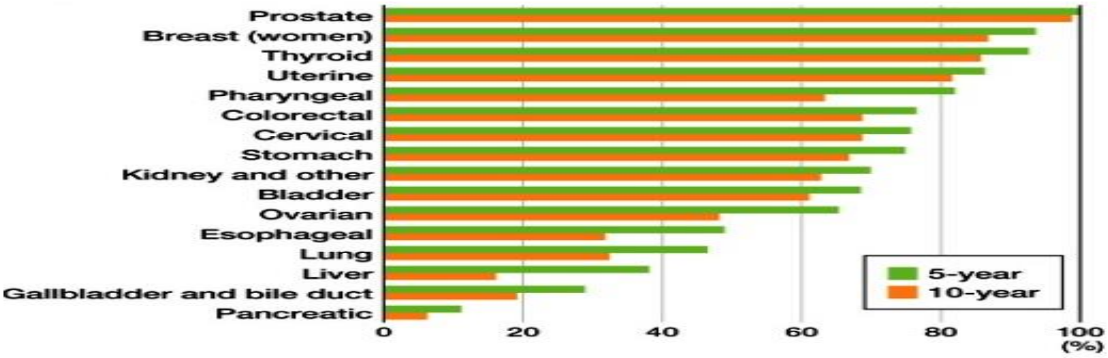


Fig. 1.3 Five and Ten Year Survival Rates of Various Types of Cancer[18]

As seen in the fig. 1.3 above, liver cancer has a very low survival rate. Another research conducted by cancer research organisation UK says that by by 2030 the mortality rate of liver cancer is going to be incresed to 40 percent while all aother cancer related mortality rates will be declined. The findings are presented in the Fig. 1.4 below.

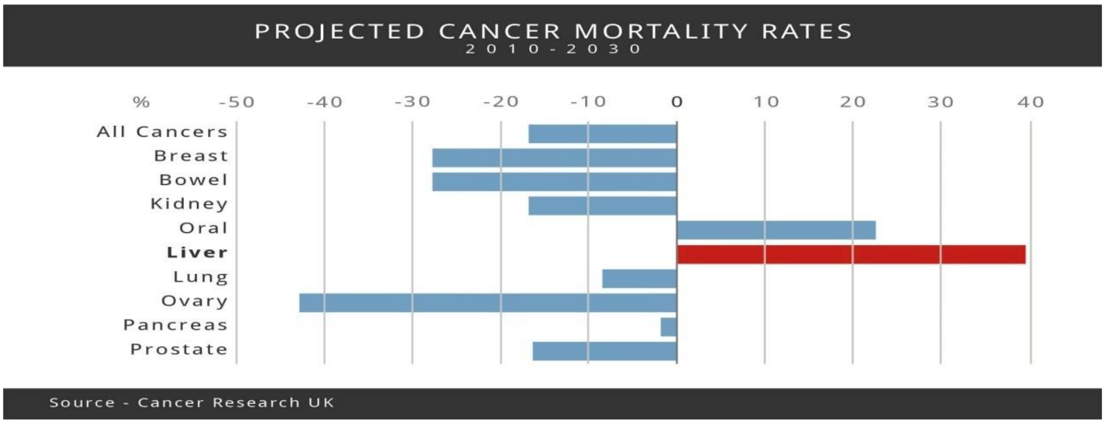


Fig. 1.4 Mortality Rates for Various Types of Cancer[18]

Another study conducted by Indian Center for Medical Research (ICMR) has shown that there is a continuous growth in the number of cancer related cases from the year 2004 to 2020. According to this study total number of cases in India will rise 1.5 million by the year 2030. Findings from the study conducted by ICMR are presented in Fig. 1.5 below.

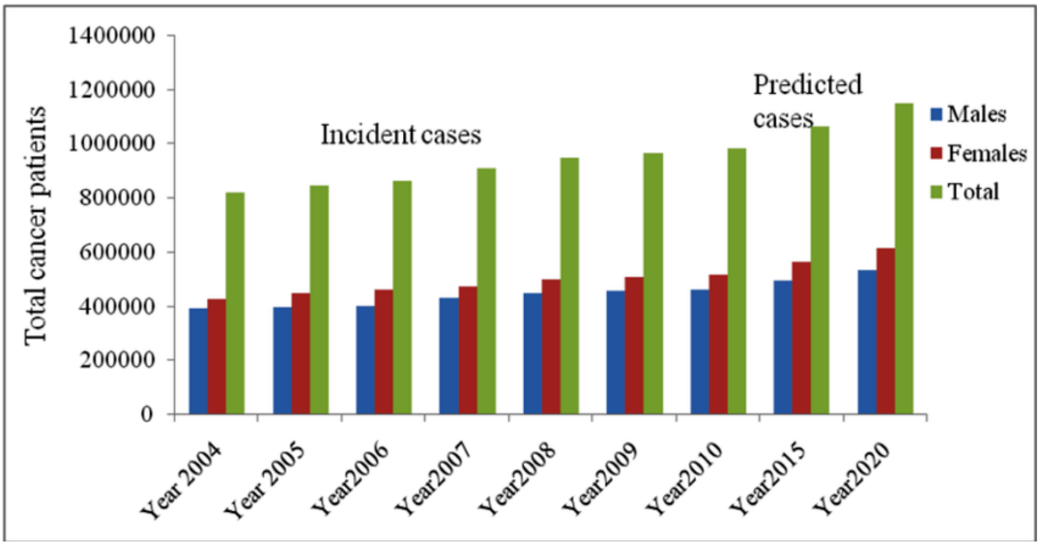


Fig. 1.5 Year Wise Growth of Cancer Cases[18]

Early detection and proper medication is the needed for solving this ever increasing problem of cancer related diseases in India and around the world.

1.2 Related Research Issues

Healthcare is not an exception to the rapid breakthroughs in AI and machine learning that have transformed many other sectors. Deep learning and computer vision are two AI techniques that have showed promise in the analysis of medical images, illness diagnosis, medication development, individualized therapy, and patient care[21]. The capacity of AI systems to handle enormous volumes of data, recognize complicated patterns, and make precise predictions has created new opportunities for improving patient outcomes and healthcare services[22].

Particularly in areas where chronic liver illnesses like hepatitis B and C infections and alcoholic liver disease are common, liver cancer poses a considerable global health burden. Because it enables prompt intervention, possibly curative therapies, and better patient prognoses, early identification of liver cancer is crucial. However, the absence of particular symptoms in the early stages of liver cancer frequently results in delayed diagnosis, restricting the range of available treatments and decreasing the likelihood of a positive outcome. Therefore, there is a critical need for a system that is more effective and precise in detecting liver cancer in its early stages[23].

The difficulties of early liver cancer diagnosis can be addressed by an intelligent system fueled by cutting-edge machine learning methods[24]. AI algorithms can help medical personnel discover suspicious lesions, characterize tumors, and offer early prognoses by examining medical imaging data, patient history, and other pertinent clinical information[25]. Such a mechanism might have a variety of effects:

- **Early Detection and Better Prognosis:** An intelligent system can help identify liver cancer early, allowing for prompt treatment and a better prognosis for the patient[26][27][28].
- **Treatment Plans:** That Are Personalized: AI algorithms can assist in creating treatment plans that are customized depending on the patient's unique situation, maximizing the efficacy of medications, and reducing adverse effects[29].
- **Reduced Healthcare Costs:** By avoiding costly and intensive therapies necessary in advanced stages of liver cancer, early identification and prompt intervention can result in cost savings[30].
- **Enhanced Decision Assistance:** Healthcare practitioners may take advantage of the system's decision assistance features, which can help with difficult situations, cut down on diagnostic mistakes, and enhance patient management[31].
- **Research and Knowledge Growth:** An intelligent system may also assist in the collection of important data for studies related to liver cancer[32].

Despite the enormous promise, creating an intelligent system for early diagnosis of liver cancer has its own unique set of difficulties. Assuring the safety and security of patient data, addressing any biases in the data, and meeting the requirement for big and diverse datasets for training strong AI models are a few of the major problems. However, these difficulties offer chances for cooperation among data scientists, physicians, and AI researchers to develop thorough and moral AI systems. Collaboration may result in the creation of precise, trustworthy, and intelligent technologies that are clinically proven and easily incorporated into current healthcare processes.

The creation of an intelligent liver cancer detection system has the potential to significantly enhance patient outcomes by early diagnosis and proper treatment. Effectiveness of liver cancer detection can be improved by utilizing modern machine learning techniques, such as ensemble approaches,deep learning and feature selection algorithms. Thoughtful data collecting, thorough algorithm validation, ethical concerns, and tight cooperation between medical experts and AI researchers are all necessary for the effective deployment of such systems. An intelligent system for liver cancer diagnosis has the potential to transform healthcare procedures and have a substantial influence on patient care in the future as AI and machine learning continue to progress.

Deep learning models frequently need a lot of labeled data for training [11] [20] [33]. Due to privacy issues and the rarity of some kinds of liver cancer, acquiring a sizable and high-quality dataset for liver cancer might be difficult [34]. By investigating methods like data augmentation, transfer learning, or semi-supervised learning to successfully use smaller datasets, research may concentrate on resolving the problem of scarce datasets [35].

Deep learning models, especially those with complicated architectures like deep convolutional neural networks (CNNs), are sometimes referred to as "black-box" models[36] because of challenges to understand the judgments they take. Research may be done to make models more interpretable and explicable, revealing the traits and patterns the model has learnt, and strengthening the reliability of the predictions.

Handling Class imbalance, where certain classes may contain much less samples than others, is a prevalent problem in medical datasets, especially those on liver cancer [37]. To guarantee that the model does not favor the dominant class, it is essential to address the issue of class imbalance. To successfully handle this issue, techniques like oversampling, under sampling, or cost-sensitive learning might be investigated.

1.2.1 Generalization to Unseen Data: It's crucial to make sure that the deep learning models created can effectively generalize to unobserved data [38]. Models should not be resistant to changes in imaging methods, patient characteristics, and other variables. By using regularization strategies, doing cross-validation trials, or investigating domain adaption approaches, research may be focused on enhancing the generalization capacities of the models.

1.2.2 Real-Time Inference: For prompt decision-making in healthcare situations, real-time inference is crucial [39]. Deep learning models, however, may be computationally demanding, and their inference time might be a constraint. In order to attain real-time speed without compromising accuracy, research might concentrate on optimizing the models for efficient inference, investigating strategies like model compression, quantization, or hardware acceleration.

1.2.3 Workflow Integration with Clinical Procedures: Integrating deep learning models seamlessly with current healthcare procedures is essential to facilitating their adoption in clinical practice. In order to provide seamless data flow and accessibility for medical practitioners, research can address the difficulties of integrating the generated models into patient monitoring system or other clinical systems [40].

Deep learning model deployment in medical contexts involves several ethical and legal issues, including patient privacy, informed permission, and liability. To assure the moral and responsible use of deep learning models in the identification of liver cancer, research can concentrate on addressing these issues and creating frameworks and recommendations.

By examining these research questions, developments may be achieved in deep learning based liver cancer detection, enhancing the established models' precision, dependability, interpretability, and usability for improved clinical results.

1.3 Motivation

Due to recent advances in the computer aided medical image analysis, and high accuracy obtained by various artificial intelligence algorithms [41], lots of research is being carried out in his field. In particular deep learning algorithms have shown significantly better results [42] when compared with certain machine learning algorithms in medical anomalies detection due to their inherent ability to find hidden features in medical images [43]. Following factors motivated us to carry out this particular research.

1.3.1 Early Detection and Better Patient Outcomes: Liver cancer is frequently discovered at an advanced stage, when the prognosis is dismal and the treatment choices are few. By allowing for prompt interventions and potentially curative therapies, early diagnosis is essential for improving patient outcomes. Deep learning models might improve early detection capabilities, improving patient quality of life and survival rates.

1.3.2 Efficiency and Automation: The manual evaluation of histological slides and medical imaging for the purpose of detecting liver cancer takes time and is vulnerable to inter-observer variability. Deep learning models can speed up and reliably automate the detecting process [45]. These models can increase efficiency and free up healthcare personnel to concentrate on other facets of patient care by lightening their workload.

1.3.3 Increased Sensitivity and Accuracy: Large datasets may be used to train deep learning algorithms to recognize intricate patterns and characteristics. They can pick up on minute details in histopathology slides and medical pictures that a human viewer would miss. The accuracy and sensitivity of liver cancer detection can be increased by utilizing the capabilities of deep learning, potentially resulting in earlier and more precise diagnosis.

Planning a customized course of therapy is necessary since liver cancer is a diverse condition with several subtypes and stages. Deep learning models can help in defining various forms of liver cancer and predicting prognosis, assisting in the development of individualized treatments[46]. These models help direct treatment choices and improve patient care by giving doctors comprehensive information about the tumour features.

1.3.4 Technologies for imaging have advanced: A lot of imaging data is now accessible for the early identification of liver cancer because to the development of cutting-edge imaging technologies such aspositron emission tomography (PET), Ultra

Sound Imaging, 3D magnetic resonance imaging (3D MRI), andcomputed tomography (CT). Deep learning models may make use of this abundant data source to glean insightful information and boost diagnostic precision[47].

1.3.5 Potential for Clinical Practice Integration: Patientmonitoring systemamong others, are already used in clinical workflows, and deep learning models have the potential to be incorporated into these workflows[48]. Through continuous data flow and decision support made possible by this integration, physicians will be able to decide based on predictions and classifications supplied by the models.

Overall, the goal of research on deep learning-based liver cancer detection is to take use of these models' capacities to increase early detection, accuracy, and sensitivity, enable personalized treatment planning, and eventually optimize patient outcomes. Researchers want to significantly enhance the diagnosis of liver cancer and contribute to the creation of more effective and efficient healthcare practices by utilizing the potential of deep learning.

1.4 Scope

The study will concentrate on creating and improving deep learning models that are especially tailored for detecting liver cancer. To construct best model, it is necessary to investigate alternative designs, including convolutional neural networks (CNNs), and other machine learning algorithms.

Acquisition and preparation of relevant medical imaging datasets, such as CT scans including instances of liver cancer, will be required for the research. For training and assessment purposes, the datasets will be meticulously selected, preprocessed, and annotated to guarantee their quality and consistency.

Correct segmentation to obtain region of interest (ROI), or the liver area, within medical imaging, is a crucial step in the liver cancer diagnosis. The study will concentrate on creating reliable and effective segmentation techniques to separate the liver area, which will be used to train DCNN models.

1.4.1 Deep learning model training and evaluation: The annotated dataset will be used to train the built deep learning models on patterns and attributes related to liver cancer. The models' efficacy in identifying liver cancer will be assessed using common metrics including sensitivity, specificity, f1 score andaccuracy.

1.4.2 Comparative Analysis: The research will compare deep learning models to conventional techniques and accepted clinical standards for detecting liver cancer. In order to comprehend the benefits and constraints of deep learning models, it will be necessary to compare their performance to that of currently used methods.

1.4.3 Interpretability and Explainability: The study will look at ways to make the deep learning models used to identify liver cancer more comprehensible and easier to understand. To gain insights and enhance the models' clinical interpretability, this will entail visualizing and analyzing the learnt characteristics and decision-making processes of the models.

1.4.4 Clinical Workflow Integration: The system being created on the basis of deep learning will be planned with attention for integration into current clinical workflows. In order to facilitate seamless data flow and practical application in actual clinical settings, this also involves interoperability with PACS, EHR systems, and other clinical infrastructure.

The construction and assessment of deep learning models for the early diagnosis of liver cancer is the main focus of the study, with an emphasis on the models precision, effectiveness, interpretability, and integration with clinical processes. The study focuses on a technology approach to improve liver cancer diagnosis using deep learning techniques rather than on the creation of new imaging modalities or large clinical trials.

1.5Challenges in Liver Cancer Detection using Deep Learning

CT images are frequently utilized to examine abdominal organs. As a result of the poor contrast in fluctuating liver area and between nearby organs such as kidney, pancreas, and muscles, liver segmentation and cancer detection in abdominal CT images is a vital challenge [49][50].Further due to change in shape, size and volume of liver of male and female [51], it becomes even more difficult to obtain ROI that can be used as input for DCNN to detect liver cancer. Following challenges have been identified and discussed in following section regarding liver cancer detection using deep learning.

1.5.1 Data Availability and Quality: Deep learning models' success is largely dependent on the availability and quality of data. It might be difficult to find a big, varied dataset containing liver cancer cases that have been annotated. The robustness and generalizability of the created models might be impacted by the dearth of high-quality datasets [52].

Deep learning models are sometimes referred to as "black boxes" because of their intricate design and great dimensionality. It might be challenging to interpret these models' decision-making processes and comprehend the underlying characteristics that support their forecasts. A difficult challenge is ensuring the interpretability and explainability of the produced models.

1.5.2 Limited Generalizability: Deep learning models may encounter difficulties when applied to other demographics or imaging methods when trained on particular datasets [53]. The effectiveness and generalizability of the models may be affected by variations in imaging methods, data gathering procedures, and demographic characteristics. To guarantee that the models work successfully in various circumstances, these elements must be carefully taken into account.

Deep learning model training and optimization frequently call for a huge amount of computing resources, such as powerful GPUs and plenty of RAM [54]. The scalability and feasibility of implementing the models in resource-limited clinical situations may be hampered by these resource needs.

Deep learning models in healthcare present a number of ethical and legal questions, notably those pertaining to patient privacy, data security, and regulatory compliance [55]. When creating and using the models in clinical practice, it is crucial to ensure compliance with ethical standards and data protection laws.

Compatibility with Existing Systems, Data Exchange Protocols, and User Interfaces Need to be considered to Ensure Seamless Integration and User Acceptance

When integrating deep learning models into current clinical workflows, there may be technical and logistical challenges.

1.5.3 Validation and Application in Real World: Although research studies may show encouraging outcomes in carefully monitored experimental settings, the application of deep learning models to everyday clinical practice necessitates extensive clinical trial validation. The use of the produced models in the real world could encounter difficulties in terms of process modifications, user acceptability, and the need for training and support [56].

To ensure the validity, dependability, and applicability of the suggested deep learning-based system for liver cancer detection, it is critical to recognize and solve these constraints during the research and development process.

1.5.4 Unbalanced data issue: Another major issue in this area of study is data imbalance. This is because, for a given task, it is more difficult to gather or locate images for the abnormal class than for the normal or healthy class. Consider the widely used ISBI 2016 dataset, which includes 248 melanoma cases and 1031 non-melanoma cases for the diagnosis of skin cancer. The CNN model is biased toward the more prevalent class (non-melanoma in the example above) due to the issue of data imbalance. Data augmentation has been widely used to address the aforementioned problems. Nonetheless, creating CNN models capable of resolving this issue remains an unsolved research issue.

1.5.5 Data annotation issue: The most difficult task has been labelling or annotating medical images, while the process of gathering and storing such images has become comparatively easier [55]. Annotations for a particular task are typically made by domain experts, such as pathologists, radiologists, etc. But labelling every image in a big dataset takes a lot of effort and time. For instance, radiologists must laboriously annotate the MRI data slice by slice in order to segment brain tumours using CNN models [56]. Consequently, it is critical to create CNN models that can efficiently learn from sparsely annotated data. Future research will also look into automatically labelling unlabelled images in the field of medical image analysis using semi-supervised algorithms.

1.5.6 Inability to explain: Conventional CNN operates as a "black box," suggesting that it withholds a clear explanation of the thinking behind its judgments or forecasts. It is challenging to trust and use CNN in clinical applications efficiently due to its lack of interpretability. Explainable AI, a technique that uses feature visualization, feature importance and saliency analysis, and model-agnostic interpretability, was developed to solve this problem. It offers transparent and comprehensible insights into the choices made by a CNN model. Few researches have examined the idea of explainable AI in relation to cancer diagnosis from medical images. As a result, a large body of research on CNN models' explains ability is anticipated in the near future, which may increase confidence and eventually motivate medical professionals to use CNN-based systems in clinical settings. In summary, CNNs have achieved state-of-the-art results in many cancer detection tasks and have had a significant influence on the medical imaging research community. Nevertheless, it is important to remember that using CNN models in real-world scenarios presents a number of challenges, including the following:

(1) Large-scale datasets are frequently required for desired performance [25]

(2) CNN model training is computationally more expensive and necessitates GPU-based hardware [55].

(3) Despite the fact that a number of methods have lately been put forth to comprehend CNN's layers and deep structure, these systems are frequently viewed as opaque. Therefore, a good strategy for this is urgently needed and would boost CNN's acceptance [28] [34] [56].

1.6 Objectives of Proposed Work

Based on the suggestions given by the expert panel members during State-Of-The-Seminar, the objectives of this research are finalized as follows:

1. To develop an efficient segmentation method for finding out the region of interest (ROI).

   (Liver is present in the stomach along with several other organs such as kidneys, pancreas, intestine etc. In order to correctly identify the type of cancer and plan proper surgery at the exact place of cancer, segmentation is necessary. Currently expert medical practioners do it manually, which is time consuming and has errors. Also proper segmentation improves accuracy of cancer detection algorithms. This is why our first objective is to develop an efficient automated segmentation technique.)

2. To design a Deep Convolutional Neural Network (DCNN) architecture for multi class liver cancer detection.

   (In recent times deep neural networks has shown most accuracy in classifying medical images. deep neural network has the advantage of identifying and extracting feature from medical images that are hard to define. This is the reason why we chosen deep neural network based classifier for feature extraction and classification)

3. To develop an easy to use system incorporating the designed DCNN architecture.

   (We understand that any such system will be deployed at the imaging centers where along with doctors, many other technicians who are not very comfortable using new systems will be our end users. Therefore we propose to design an easy to user interface that will require minimal inputs for using the system.)

4. To validate the designed system through extensive comparative analysis using standard metrics.

   (In order to validate proposed system, we have implemented several other machine learning algorithms along with proposed classifier on primary and secondary data. We have compared the results of our own implementation and also compared the results of our classifier with state of the art from reputed research articles. Findings are presented in chapter 5 with detailed discussion.)

1.7 Thesis Organization

The thesis organization proceeds as mentioned: Chapter 2 presents the survey of various Liver Segmentation and Cancer Detection Methods.Chapter 3 explains the pre-processing and Segmentation methods used in proposed technique. Chapter 4 explains the proposed classifier. Results and various performance evaluation metrics are discussed in detail in Chapter 5. Chapter 6 gives the conclusions and possible future research scopes.

1.8 Summary

In this chapter we have discussed in detailed about the background study of liver cancer detection, types of liver cancer, various methods used for liver cancer detection, various study conducted to show the magnitude of the problem. Discussions regarding motivations to carry this research are explained in this chapter. Various challenges in creating a system based on DCNNare discussed. Finally based on extensive literature and suggestions from expert panel, our research objectives and reasons as to why we finalized those objectives for our research is explained.

Chapter 2

LITERATURE REVIEW

A number of studies are conducted utilizing deep learning (DL) and machine learning (ML) techniques for the segmentation of the liver and the identification of liver tumors. The recent work that has been used for liver segmentation, cancer detection, and medical image pre-processing is highlighted in this section.

2.1 Survey of Medical Image Pre-Processing

Sezal et al., [57] address an overview on clinical picture de noising utilizing different channels and Wavelet Change. This paper gives the audit of different de noising strategies, for example, various Channels and Wavelet change. Manyu et al., [58] present another picture denoising strategy using Gaussian channel. This paper proposes a new de noising calculation using Gaussian channel and NL-implies channel. As a general rule, the exploratory outcome shows that this technique is better than Gaussian channel alone and NL-implies channel alone , as it is neither like Gaussian channel which is not easy method to detect edge, nor as the NL implies channel which can't take out noise without keeping actual structure. Arin et al.,[59] introduced de-noising of clinical pictures by utilizing a few channels. In this method various sorts of channels were utilized to eliminate the commotions, for example, normal channel, Gaussian channel, log channel, middle channel, and wiener channel.

This paper showed that the Gaussian channel is a reasonable channel to eliminate the commotion in the clinical pictures. The straightforward wavelet based sound decrease was proposed by weaver et al.,[60]. The principal downside of this sifting strategy was that any little designs that are comparable in size to the commotion of image. Anja et al.,[61] proposed Wavelet Based Sound Decrease in CT-Pictures Utilizing Connection Examination. In CT two spatially indistinguishable pictures can be created by recreations from disjoint subsets of projections. For standard CT-scanners the two pictures can be produced by separating the arrangement of projections into even and odd numbered projections. The subsequent pictures show a similar data however contrast picture color. The investigation of relationships between the wavelet portrayals of the info pictures permits isolating data from commotion down to a specific sign to-clamor level. V Naga et al., [62] introduced denoising of clinical pictures utilizing double tree complex wavelet change. It utilizes double tree complex wavelet change to break down the picture and shrinkage activity to take out the commotion from the uproarious picture. In the shrinkage step they utilized semi-delicate and stein thresholding administrators alongside customary hard and delicate thresholding administrators and confirmed the appropriateness of double tree complex wavelet change for the denoising of clinical pictures. The outcomes demonstrated that the denoised picture utilizing Double Tree Complex Wavelet Change(DTCWT) have a superior harmony among perfection and precision than the DWT and less excess than Undecimated Wavelet Change(UDWT) [63].It utilizes double tree complex wavelet change to deteriorate the picture and shrinkage activity to kill the commotion from the boisterous picture. In the shrinkage step they utilized semi-delicate and stein thresholding administrators alongside customary hard and delicate thresholding administrators and checked the reasonableness of double tree complex wavelet change for the denoising of clinical pictures. The outcomes demonstrated that the denoised picture utilizing DTCWT have a superior harmony among perfection and exactness than the DWT and less repetitive than UDWT. J.mohan et al.,[64] gives an overview on the attractive reverberation picture denoising strategies. This paper presented about attractive reverberation imaging and the attributes of commotion in X-ray, the famous methodologies are characterized into various gatherings and an outline of different strategies is given. The denoising technique's benefits and restrictions are likewise examined. Rajeshwari S. etal., [65] introduced a strategy to further develop the picture quality by denoising and goal upgrade. This paper thinks the normal, middle and wiener sifting for picture de noising and an introduction based Discrete Wavelet Change (DWT) procedure for goal upgrade. Table 2.1 below shows the summary of literature review of various image pre-processing techniques.

Table 2.1 Summary of Literature Review of Various Preprocessing Methods

Author	Area	Approach	Pre processing	Application	Accuracy
Penget al.,2023[31]	Image classification	CLIQUE grid	Color pelleting	automatically convert colloquial descriptions into color palettes	98%
Wei et al., 2023[32]	Image classification	CNN	Edge Detection	Low complexity illumination invariance detection	97%
Hui et al., 2023[40]	Image Augmentation	CNN	Edge Detection	Multi sensor data fusion	96%
Iwasa et al.,2022[34]	Image Augmentation	CLIQUE grid	Color pelleting	Image Comparison	97%
Wang et al., (2021)[22]	Image Augmentation	Random Implication Image classifier	Median filter	Iris disease detection	96.7%
Poloni et al., (2021)[20]	Image Augmentation	SVM	Non-Local Means technique	Alzheimer's disease diagnosis	69.44%
Beeravolu et al., (2021)[25]	Image Augmentation	Deep CNN	Sobel filter	Breast cancer classification	99.06%
Heidari et al., (2020)[21]	Image Augmentation	CNN	Gaussian low-pass filter	X-Ray classification on COVID 19	94.5%
Manoharan, S. (2019)[28]	Image Augmentation	SVM	Bayesian Filter	Automobile leak detection	98%
Jacob, I. J. (2019)[42]	Image Augmentation	Capsule networks	Fuzzy image filter	Biometric recognition	99%
Sinagaetet al., 2019 [43]	Image classification	unsupervised k-means algorithm	Color Block Clustering	automatically finding an optimal number	94%
Hui et al., 2019 [45]	Image classification	Modified K-means clustering algorithm.	Color Block Clustering	Image Comparison	96%

2.2 Survey of Liver Segmentation

The liver and other body parts can be seen on abdominal CT scans. To properly extract the properties of the liver, the liver portion of the CT scans must be segmented. Graph cut method proposed by Guodong et al., 2015[68], Laplacian mesh optimization by Gabriel et al., 2016 [67], active contour model by Assaf et al., 2016 [66], and 3D liver segmentation proposed by Zhang, 2017 [69] are some of the methods that have been used in the past to segment the liver from abdominal CT images using deep learning algorithms.

More attention has been focused on unsupervised deep learning algorithms for liver segmentation, since they have demonstrated superior performance compared to conventional segmentation techniques. According to Kaijian et al. (2017) [70], unsupervised Deep Adversarial Networks (DAN) combined with Weighted Loss Function (WLF) provided the semantic liver segmentation on abdominal CT scans. Additionally, Wang et al., 2018 proposed the use of convolutional neural networks (CNNs) for the segmentation of lesions in liver CT images, resulting in a dice similarity coefficient of 80.06% [71]. As suggested by Lu et al., 2019 [72], it is noticed that the combination of a DL algorithm with graph cut refinement boosts the efficiency of liver CT image segmentation.

The peri-hepatic structure is regarded as the background component in the graph-cut approach, whereas the liver portion is approximately regarded as the foreground. Then, in the homogenous zones, the foreground and background pixels are separated using cut algorithms, as suggested by Boykov et al., 2020 [73].

For the purpose of determining the liver's texture, intensity-based approaches compare the gray intensity value of each pixel to the intensity of nearby pixels. An specialist in the liver parenchyma places the seed points by hand in these approaches. The homogenous texture region is made up of a group of pixels that are grouped together and match the seeds. Per Lopez et al.'s (2021) proposal, this system was semi-automatic in nature, and its performance relied on manual seed points. Often, intensity-based approaches led to leakage in the edges and manually seeded region due to the lack of the shape control option. The results of Sharma and Agarwal's 2020 study [75] indicate that intensity-based approaches are not appropriate for MR images with very diverse textures.

AI based strategies, for example, support vector machines (SVMs) proposed by Defeng et al., 2022 [76] and an irregular backwoods strategy proposed by Norajitraet et al., 2019 [77] has been effectively introduced for the quantitative component extraction of the picture surface. These calculations have given better execution and exceptionally discriminative capacity than the power based techniques. Once in a while, due to the commotion and pivot this technique can prompt the spillage or coarse division. As of late, CNN was introduced for the liver division to remove the quantitative highlights as opposed to hand-created highlights. It could fragment heterogeneous liver surface in least stretch of time as proposed by Elshaer et al., 2022 [78].

In a new review report, a few DL approaches like profound DCNN, auto encoders (AE), completely convolutional network (FCN) and profound conviction organizations (DBN)were introduced for disease discovery and examination by Hu et al., 2018[79]. As of late profound learning and inclination based liver division was finished to accomplish exact forms of liver and cancer inside. An original 3D CNN has been explored for the essential and optional liver malignant growth location utilizing dissemination weighted X-ray (DW-X-ray). It has shown critical improvement (83%) in the liver recognition rate as proposed by Eleftherios et al., 2020 [80]. They tended to lopsidedness issue in division and dissected that re-weighting and closeness based estimation as misfortune capability isn't better strategy as seen by Zhang et al., 2020 [81]. Once more, to manage the awkwardness interestingly, and recurrence events, overflow U-ResNets has been introduced for the liver division and sore division by Xue-feng et al., 2022 [82].

Table 2.2 Summary of Literature Review of Various Liver Segmentation Methods

Author and Year	Application	Methodology	Evaluation Metrics	Performance
Li et al., 2023[85]	Liver Segmentation	SSC and Graph cut based technology	VOE% RVD%	9.2% 0.5%
Liu et al., 20203[72]	Liver Segmentation	Optimized Neural Network	Dice Score	0.86
Ranjbarzadeh et al., 2023[53]	Liver Segmentation	fuzzy c-means and mean shift clustering	average surface distance (ASD), Volume overlap error (VOE),	ASD=0.4 VOE=4.5
Eleftherios et al., 2022[80]	Liver Segmentation	3D Convolution Neural Network (3D-CNN)	Dice Score	83%
feng et al., 2022[76]	Liver Segmentation	cascade U-ResNets	(VOE), (RVD), and (DC)	VOE=O0095 RVD=0.021 DC=94.9
Zhang et al., 2022[69]	Liver Segmentation	Inception Net	Area Under Curve	89.7%
Kaijian et al., 2021[70]	Liver Segmentation	Unsupervised Deep Adversarial Networks (DAN)	Dice Score Volume Overlap Error (VOE)	97.00% 7.90%
Wang et al., 2020[71]	Liver Segmentation	convolutional neural network (CNN)	Dice similarity coefficient	80.06%
Lopez et al., 2019[74]	Liver Segmentation	Intensity based technique	VOE,Relative Volume Difference (RVD),	6.28 % -2.38 %
Jie L, 2018[80]	Liver Segmentation	Support Vector Machine	True Positive Rate	96.1 %

2.3 Survey of Liver Cancer Detection

For the liver malignant growth identification different surface, shape and inclination based highlights have been extricated with the assistance of different shallow and profound learning calculations.

A computer aided frameworks in light of auto-covariance surface highlights introduced for the liver malignant growth identification in crude and non-pre-handled CT pictures. Co-fluctuation based highlights are utilized for the inconsistency catching of the liver surface picture. Co-fluctuation based technique frequently experienced the enlightenment changes, obscure, unfortunate differentiation, direction and size of the liver picture. Auto-covariance surface highlights brought about an exactness of 81.7% (Huang et al., 2018) [83]. A molecule swarm streamlining (PSO) technique was utilized for the hepatocellular carcinoma identification in liver pictures. PSO can yield the improved arrangement alongside other calculation and can find the ideal boundaries which can give better malignant growth identification rate. Maybe, execution of PSO isn't ensured and it might get trapped in the neighborhood minima, it needs more emphasis for the learning. It was seen that occurrence streamlining (IO) and SVM given better execution for liver malignant growth identification (Jiang et al., 2019) [84].

Moreover, a method for segmenting the tumor, cyst, and normal liver using an edge-based distance regularized level-set evaluation has been introduced. The liver's texture and shape are correlated, as demonstrated by edge-based distance as proposed by Li et al., 2023 [85]. The detection of liver tumors has significantly improved with the use of a multi-channel fully convolutional network (MC-FCN) model. The shallow learning algorithm that convolutional networks belong to helped to describe the properties of the ensemble texture and improve the local representation of the raw features as proposed by Khan et al., 2022. [86]. Several statistical methods have been employed for statistical attribute extraction, including the gray level co-occurrence matrix (GLCM). The characteristics of GLCM included homogeneity, correlation, entropy, and energy. The liver is frequently depicted using a gray level intensity CT pictures that can depict the borders, contours, and subtle variations in the texture of liver images. For systems with small databases, it is reliable, stable, and easy to implement. Due to the requirement for user interaction, noise, blur, uneven intensity distribution, and contrast of the CT images, the performance of GLCM-based systems is limited. The system's performance is reduced when the foreground or background are smaller (Dong et al., 2022) [87].

Algorithms based on learning are more appropriate for detecting liver cancer. When back propagation neural network (BPNN) and support vector machine (SVM) performance is compared for liver tumor detection, BPNN performs better than SVM (73.23% accuracy).The time needed for training and testing BPNN is greater even though it performs better than SVM in terms of accuracy. Compared to SVM, the BPNN requires more parameter tuning (Devi et al., 2019) [88]. The proper tuning of the Support Vector Machine, as suggested by Rajagopal et al., 2020 [88], produced an accuracy of 97.83% for the detection of liver tumors in CT images. An automatic fuzzy clustering scheme and a multi-SVM classifier have been presented to address the under segmentation problem in the classification of liver diseases, including hem, cyst, and HCC (Sakret al., 2020) [89]. According to an analysis of conventional machine learning-based methods, the effectiveness of the system for detecting liver cancer is largely dependent on the raw features that are extracted usingalgorithms for extracting features. Less uniqueness and correlation exist between raw features in the local feature representation.

Prior research on deep learning algorithms was widely used to classify liver cancer based on conventional features (Kaizhi et al., 2019) [90]. Improved scarcity and ease of implementation characterize Fully CNN (FCNN). With the aid of 3D liver segmentation, it has demonstrated improved performance for the lower database (Dong et al., 2022) [91]. According to Abdulgani et al. (2021) [92], the Hybrid Feature Selection approach (HFS) based on neural networks has been effectively used for the detection of liver cancer. The liver tumor segmentation technique then presented multi-scale candidate generation (MCG) with the aid of super-pixel segmentation, which made use of an active contour model (ACM) and 3D fractal residual network.In ResNet. It reduces computation complexity brought on by redundant data and increases the deep network's sensitivity to identify liver tumors (Rozjan al., 2018). 93]. additionally, a deep learning-based combination of the watershed transform (WT) and gaussian mixture model (WT-GMM) has been used to detect the liver lesion. According to Das et al. (2019) [94], the recognition rate was

99.38 percent. Many conventional and machine learning based methods have been presented for computerized automated liver tumor detection due to the variety of liver cancers and liver images (Das et al., 2018) [95]. Gunasundari et al.,, 2015 [96] highlights the role that natural computing techniques and bio-inspired computational methods play in the detection of cancer in medical images. Dimensionality reduction, a recent development in image analysis and recognition, was demonstrated by CCN (Ali et al., 2017) [97]. Recently, real-time CT image contrast has been improved through the use of non-sub-sampled contour transform and multi-scale image fusion to improve the edge information (Jin et al., 2016) [98].

Due to a variety of factors, including liver stretch and slight ferocity divergence between lesions and surrounding tissue, automatically segmenting liver lesions is a challenging task. Better performance for liver lesion detection in extremely difficult conditions has been instilled in deep learning architecture based on probabilistic neural networks (Wu et al., 2011) [99]. Additionally, deep inception net has been investigated for the detection of benign and malignant HCC liver cancer, with 96% accuracy. In HCC, ten frequently occurring prognostic genes were predicted using the inception network. Research has demonstrated that CNN can assist with the identification and categorization of gene mutations in liver cancer (Chen M., 2020) [100]. Afterwards, the impact of deep learning has been demonstrated to help pathologists differentiate between hemato-xylin, eosin-stained whole-slide images (WSI), and hepatocellular carcinoma and cholangio-carcinoma. Conventional machine learning algorithms possess redundant features and incur significant computational costs. Recent deep learning models that address these issues are having trouble with network hyper-parameter optimization and network topology. As a result, LeNet-5/ABC, a hybrid algorithm combining the LeNet-5 model and the ABC algorithm, was proposed (Ghoniem R., 2020) [101] for the detection of liver lesions. Subsequently, a deep learning model for cancer detection and liver segmentation that uses three UNets was presented. According to Ayalew et al. (2020), they used three UNets: one for liver segmentation, two for tumor segmentation from segmented liver, and three for tumor segmentation from full abdominal images [102]

Table 2.3 Summary of Literature Review of Liver Cancer Detection Methods

Author's	Feature Extraction	Classifier	Key Features	Limitations
Li et al., 2023 [85]	CNN	DCNN	High accuracy of 97% for given data set	Multi class cancer detection not performed.
Liu et al., 2023[72]	CNN	DCNN	Model works for 2D and 3D images as well	Pre-processing and segmentation not discussed
Khan et al., 2022 [86]	GLCM	FCM, Slope difference distribution (SDD)	Autoliv a new model for segmentation was proposed	Feature extraction not discussed
Dong et al., 2022[91]	DCNN	FCNN	Training of FCNN for segmentation and classification is discussed in detail.	Feature extraction not discussed
Abdulgani et al., 2021 [92]	optical transmittance	Prony's Algorithm	Behaviour of light was studied when it passes through tumor cell	Very difficult to generalize result as volume, shape and size of tumor varies from patient to pateint.
Das et at., 2019 [95]	LBP-HF	Decision Tree	Handles noisy and smooth data efficiently for feature extraction.	Results given for small data set.
Rozjan et al., 2018 [93]	GGCM and Gray Scale Histogram.	Decision Tree	Handles noisy and smooth data efficiently for feature extraction.	Accuracy decreased large data set
Das et al., 2018 [95]	GLCM,Morphological	Neural Network	Handles both CT and MRI image data set.	Requires large training time. Accuracy increases with size of database.
Ali et al., 2017 [97]	DWT	SVM	Classification accuracy is high up to 92%	Feature extraction requires lot of pre processing
Jin et al., 2016[98]	Gray, Texture	Random Forest	Works very well for 2D CT images.	Very sensitive to noisy data. Requires lot of pre-processing.
Gunasundari et al., 2015 [96]	FOS combined with the Co-occurrence based feature	PNN	Handles 2D CT images very well for feature extraction.	Large Training time required.
Wu Qiu et al.,2011 [99]	FOS,GLCM, GLRLM, GLDM and LAWS	SVM	Classification accuracy is high up to 92%	Feature extraction requires lot of pre processing

2.4Research Gaps

In above literature review various liver cancer detection techniques have been discussed which focus on the methodology, database, performance analysis, advantages and disadvantages of the techniques. Research Gaps identified on the basis of above studies are:

- Traditional AI based approaches rely greatly on data.[74] [80][103].
- Traditional methods performance suffers due to the low contrast, blur, and illumination variation, size of liver, scale and orientation of image. To deal with these issues various pre-processing strategies have been employed which adds additional computational efforts [85] [104].
- Very limited performance was recorded in case of multiple tumor located in close proximity to each other and if the size of tumor is very small [105].
- Performance is influenced by the database's size. It is difficult to access the larger database, though. Traditional machine learning algorithms become more complex as database size increases[106][107][108].
- For larger, noisier databases, shallow or deep learning-based techniques provide subpar optimized results. Again, performance of detection of liver cancer massively depends on segmentation of liver. Under-segmentation or over-segmentation leads to poor cancer detection rate [109][110][111].
- Previous segmentation techniques resulted in poor segmentation of boundary tumor in liver images and improper vessel segmentation.
- Multiclass cancer detection is challenging which helps to take proper preventive measures in specific way [112].
- Longer recognition times are caused by subpar features and parameter optimization. The performance of recent deep learning models is difficult because of network topology and network hyper-parameter optimization [114].
- There is less interclass variability and more intraclass variability with recent deep learning techniques [115].

2.5Problem Statement

From the extensive literature survey it is observed that liver cancer detection is challenging because of poor feature representation, correlation and connectivity. Further, limited performance for larger and noisy database increases the challenges of liver cancer detection systems. For the multi-class liver cancer detection using the DL framework, very little work is done.

Problem of appropriate robust and generalized method for liver cancer detection is rarely observed. Hence new method which is based on deep learning algorithm is presented for the robust multiclass liver cancer detection. Also it is observed that preprocessing noisy data and segmenting the input medical images are very challenging. As a result, we suggest developing a system that can quickly and accurately preprocess, segment, and classify incoming CT images. A range of metrics are employed to assess each process's performance. The structural similarity index (SSIM) and mean square error (MSE) are used for preprocessing peak signal to noise ratio (PSNR).For segmentation dice score, volume overlap error, jaccard index is used. For classification accuracy, sensitivity, specificity, and f1 score is used. Based on extensive literature survey, the problem statement for this research has been finalized as“To develop an efficient system to preprocess, segment and classify input CT images in order to detect multi class liver cancer fast and accurately. Also to achieve above 99% accuracy for classification of multi class liver cancer".

2.6Summary of Literature Review

In this chapter, findings of our extensive literature review which consist of more than 200 research articles from the past ten years to the current year has been presented. Literature review has been divided into three parts a) preprocessing b) segmentation and c) classification. For all three steps an extensive literature survey for various possible approaches, there benefits and drawbacks and scope of improvement has been founded. All the findings from the literature review have been in the form of three tables that summarizes our findings for preprocessing, segmentation and classification. Based on this literature review gaps, challenges and objectives of our researchhave been finalized which are discussed in detail in chapter 1.

Chapter- 3

PROPOSED SYSTEM AND METHODOLOGY

In this chapter we have discussed in detail, the proposed system and research methodology. Particularly this chapter focuses on preprocessing and segmentation part of our system. Classification is discussed in detail in the next chapter. All the steps involved in preprocessing and segmentation and various matrices that have been used to evaluate the performance of preprocessing and segmentation are discussed in detail in this chapter.

3.1 Introduction

The preprocessing and segmentation methods have been used to create an intelligent system for the detection of liver cancer. Through the removal of noise, improvement of contrast, and standardization of picture quality, preprocessing is essential in preparing medical images for analysis[116]. In order to enable targeted analysis on the particular area of interest, segmentation is then utilized to separate out hepatic region from original image[117].The liver images are enhanced in the preprocessing stage using a variety of methods, including image normalization, denoising, and histogram equalization[118]. These techniques aid in minimizing undesirable variances and highlighting the photos' key characteristics. Preprocessing is followed by the liver segmentation procedure, which precisely defines the borders of the liver[119]. This procedure is essential for separating the liver area from other tissues or structures that can obstruct the identification of malignancy. To obtain accurate liver segmentation, approaches including thresholding, region growth, or active contour models are used.

In medical practice, liver segmentation from medical imaging has made great strides. Its goal is to extract useful data about the human body for a variety of uses, including early illness identification and selecting the most effective treatment modalities. There are a number of techniques available for medical image processing, each with unique benefits and drawbacks. Ultrasound,X-rays, MRI, positron emission tomography (PET), computed tomography (CT), PET-CT, are examples of commonly utilized imaging modalities [120].For the diagnosis of a number of liver disorders, including hemangioma, focal nodular hyperplasia, adenoma, carcinoma of the liver, intrahepatic gastrointestinal cancer, and hepatic metastases, CT, US, and MRI are routinely used. Due to its high sensitivity (93%) and specificity (100%) in comprehensive exams to determine the extent of local involvement and rule out the presence of liver and extra hepatic metastases, contrast-enhanced CT imaging is one of these modalities that is frequently utilized [121]. For the purpose of finding liver cancer, CT scans are also often used.

The deep CNN is used once the hepatic region has been effectively segmented [122]. The CNN model can learn and recognize complex patterns and features suggestive of liver cancer because it was trained on a vast collection of annotated liver images [123]. Multiple convolutional and pooling layers make up the deep CNN, which uses segmented liver pictures to extract high-level information. After being fed into fully connected layers for classification, these attributes are used to detect if cancer is present or not [124].This intelligent system can successfully identify liver cancer in medical imaging data by fusing the strength of deep learning with preprocessing and segmentation methods. Early diagnosis and intervention are possibilities, which would allow for prompt treatment and better patient outcomes.

3.2 Proposed Methodology

The liver cancer detection system is implemented in two phases such as training phase and testing phase. The diagnostic flow and process flow diagram of the generalized liver cancer detection system is given in Fig. 3.1. In the training phase, all liver CT images from the training data are processed and DCNN is trained. In the training, Learning of DCNN is achieved using mini-batch gradient descent method to update the weights and parameters of deep convolutional neural.

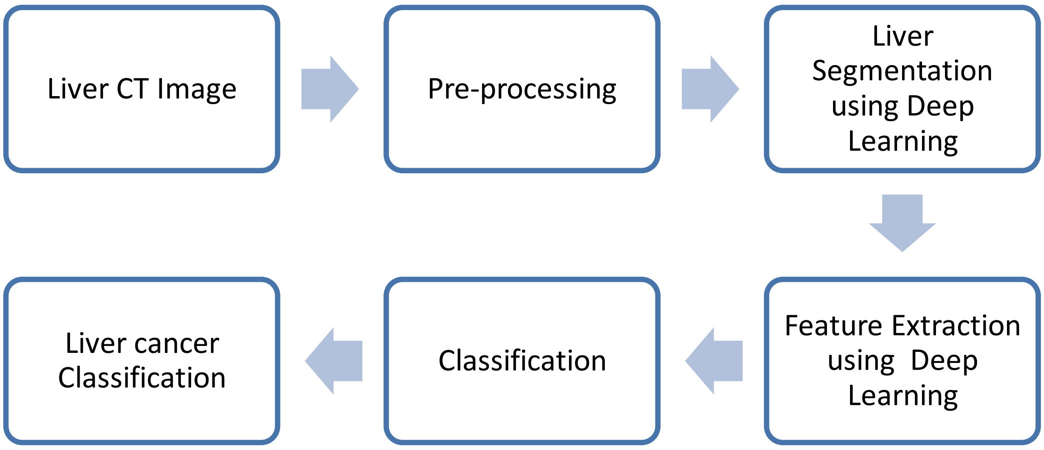


Fig 3.1 General Flow Diagram of Cancer Detection using Deep Learning[125]

Figure 3.2 below presents proposed methodology utilized for multiclass liver cancer detection using deep convolutional neural network. Various steps shown in figure are discussed in detail in the section below.

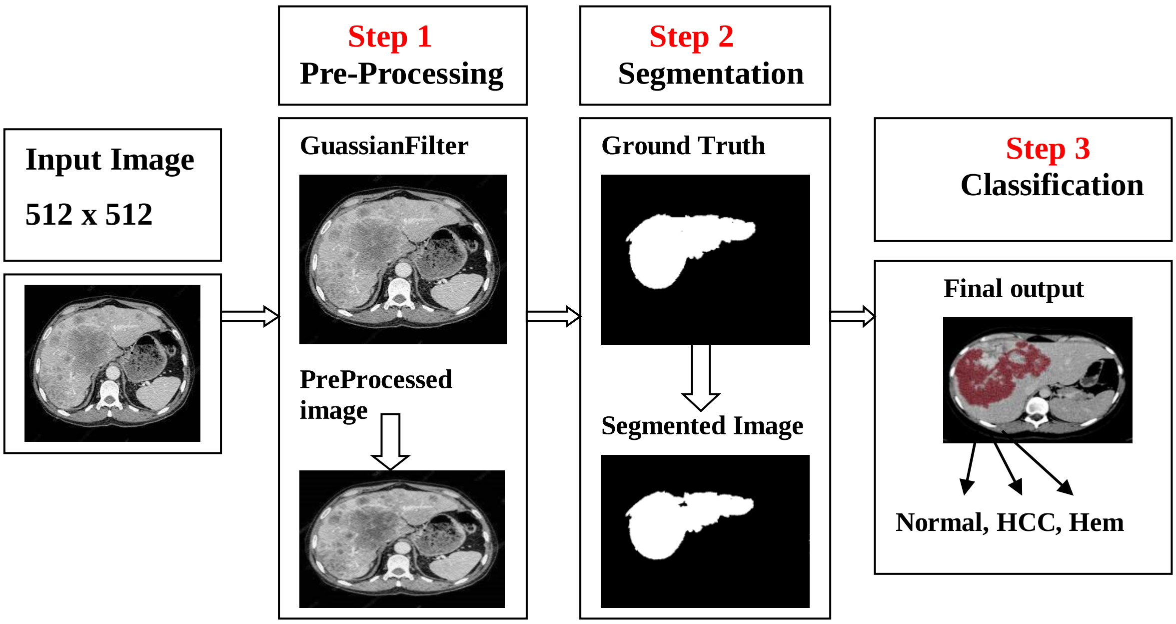


Figure 3.2: Proposed Methodology for Multiclass Liver Cancer Detection

a) Inputs and Data Collection

For developing proposed system we have used various types of primary and secondary dataset. Primary data has been obtained from Life Line Super Specialty Hospital, Kamptee, Nagpur. We would also like to express our gratitude towards the oncologist from life line hospital for providing there valuable inputs without which it would not have possible to develop this system. Secondary data has been downloaded from kaggle.com. For preprocessing and segmentation we have used Lits Dataset and for classification we have used TGCPA dataset. Additional 500 images have been generated using image augmentation techniques. Overall more than 3000 CT images have been used to train test and validate our system.

b) Pre-processing

Liver images are converted in to gray color image to avoid the time consumption and reading complexity of the three dimensional color mapped image. Again CT color images looks like the gray images and color do not carry any significance to describe the image. Due to this some information loss may take place which results in low performance of segmentation and classification algorithms. Also noises may be acquired during image capturing process either because of human error or to some technical issues such as wrong input. It is therefore necessary to remove this noise and preprocess medical images before using them for segmentation and classification. For preprocessing we have proposed a new technique based of three different filters. Preprocessing is discussed in details in the following chapter.

c) Segmentation

In the next step liver region is segmented using segmentation algorithm that can segment the complete region of interest for the further processing and neglects the other parts of the abdominal CT images to minimize the computational complexities**.** For the segmentation unsupervised watershed transform can be used. Marker controlled watershed algorithm will be used for segmentation of the liver area from the stomach CT image. The segmentation is performed until the better region is obtained or maximum iterations finished. The performance of the segmentation can be improved using the morphological processes such as area opening, erosion and dilation to minimize the unwanted part from the segmented region of interest; and to minimize the noise as well as artifacts present in the segmentation.

d) Deep Convolution Neural Network

Further, the DCNN architecture is used for the learning the discriminative representation of the liver CT images**.** To capture the local changes of the liver texture parallel DCNN architecture which consist of different hyper-parameters for the each parallel layers of DCNN. The hyper-parameters for the DCNN are number of convolution filters, size for convolution features, striding value for convolution filtering, activation function, pooling window type, pooling window size, learning rate, iterations etc.Each parallel branch consists of multiple CNN layers to learn the features of the liver images that help to decrease the intra-class variability and exploit the inter-class variability of deep learning architecture.

The DCNN architecture includesconvolutional layer, rectified linear unit layer (ReLU), maximum poling layer, fully connected layer and classification layer. The convolution layer gives the correlation or connectivity between local regions of the segmented liver image. In convolutional layer input image is convolved with the multiple convolution filters. The convolution operation takes place by sliding the convolution windowover the complete image. The performance of the convolution layer can be evaluated for the different number of the convolution filter, size of convolution filters and striding value of convolution window over the image.

ReLU is further employed to removes the linearity in the convolutional layer output. In maximum pooling layer the salient features are extracted from the ReLU layer. It minimizes the dimension of feature map. Again the performance of the system is compared for the different types of pooling such as average pooling and different sizes of pooling window. In fully connected layer, each neuron from each layer of maximum pooling layer is connected together. Fully connected layer gives the internal connectivity between different layers of the CNN.

e) Classification

For feature extraction and classification we have used DCNN. The classifier is trained for optimal parameters during training of the system and trained model is used for the testing. Final stage consists of the recognition ofmulti class liver cancer.

f) Performance Evaluation

The performance of the liver cancer detection system is evaluated based on various evaluation metrics for segmentation and cancer detection such as cross validation accuracy, F1 Score, Sensitivity, Specificity, Dice Similarity Coefficient (DSC), Relative Absolute Volume Difference (RAVD) and Volumetric Overlap Error (VOE).

3.3 Image Preprocessing

In the proposed research there are two types of dataset were been in used for detection of liver cancer in early stage and provide the medication to the patient. The dataset collected for the said research, as primary as synthetic dataset collected from the NCI, Nagpur and Secondary source of data available on kaggle as LiTs dataset. In the every research, the preprocessing stage is the first most important stage; in traditional or existing preprocessing techniques not provide the accurate input to the method. In this research a novel approach or preprocessing called as double stage gaussian filter with texture and contrast enhancement (DSGFTCE). Fig. 3.2 shows various steps involved in preprocessing CT images.

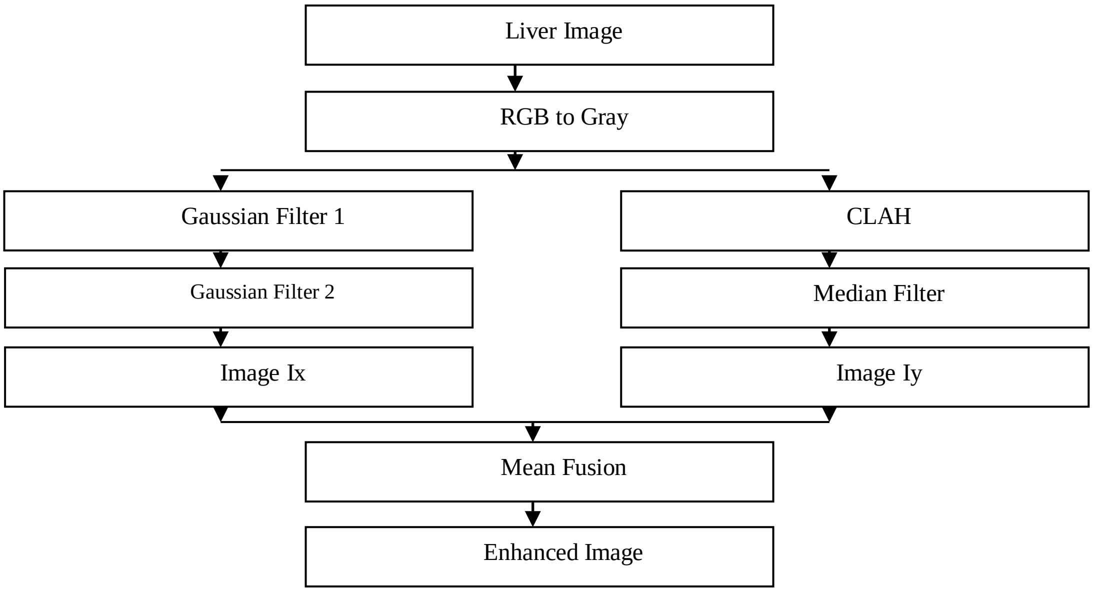


Fig. 3.3 Flow Diagram of Proposed Pre-Processing Method

In order to improve the quality of raw medical images for analysis, image preprocessing is essential. Several approaches are used, including noise reduction, picture enhancement, normalization, and standardization. These preprocessing steps are crucial for medical image analysis because they have a direct impact on the subsequent blocks and feature extraction procedures. In order to improve classification algorithms, normalization and distribution processes are used to modify the image's values and lower its dynamic range. The classifier can effectively learn and distinguish features if the picture values are standardized. Medical picture preprocessing requires the use of noise reduction techniques since they improve image resolution and get rid of undesirable parts. As a result, following processing tasks like edge identification, segmentation, and compression become more accurate. Spatial domain and spectral domain are the two primary methods for noise reduction in medical imaging. Numerous filtering techniques, including mean sorting, adaptive median filtering, order-statistic sorting, adaptive scaled median filtering, maximum a posteriori sorting, nonlinear dispersion, geometric filtering, and others can be used in the spatial domain approach. These methods try to reduce noise while keeping crucial visual elements.

3.4Double Stage Gaussian Filter with Texture and ContrastEnhancement

Proposed preprocessing method is based on DSGFTCE, which improves the contrast and texture details in an image. It combines the noise-reduction and blurring characteristics of a Gaussian filter with extra processes to improve texture and contrast [126]. Contrast limited adaptive histogram is used to remove irregularity in brightness of image. Median filter is applied to remove salt and pepper noise in the image [127][128][129]. Finally images from all the filters are combined using mean fusion technique to obtained enhanced image which can be used for preprocessing. All the steps and mathematical equations as well as evaluation parameters are mentioned in following section.

3.4.1 Double Stage Gaussian Filtering

Due to its simplicity, ease of use, and stability in generating desirable results, Gaussian filters are frequently used for filtering many sorts of surfaces [130]. In reality, for many applications requiring surface characterization, Gaussian filtration is frequently the best option. The linear Gaussian filter, which has acquired popularity and evolved into an industry standard for filtration, is widely used in research [131]. Convoluting the measured surface with a Gaussian weighting function efficiently incorporates the necessary filtering properties when applying Gaussian filters to input surfaces as shown in eqn. 3.1.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma 21}} \exp\left(-\frac{x^2}{2\sigma 2x2}\right) \qquad (3.1)$$

In equation 3.1, G(x) denotes the Gaussian function, where x is the input variable, denotes the Gaussian distribution's standard deviation, and is a constant denoting pi (roughly 3.14159) [132]. The standard deviation is taken into account while calculating the value of the Gaussian function for a given input x in order to manage the form and spread of the Gaussian curve.

Double Gaussian filters are a particular kind of image filtering method that involves running an image through two Gaussian filters in quick succession. This method is frequently used to achieve particular filtering effects and improve image quality in image processing and computer vision applications.The idea of double Gaussian filters will be discussed in this talk, as well as their benefits and practical applications. Due to their simplicity, efficiency, and adaptability; Gaussian filters are frequently used in image processing. They are frequently used for operations including feature extraction, noise reduction, and image smoothing. A Gaussian kernel, which is a matrix illustrating the contours of a Gaussian distribution, is convolved with an image to operate the Gaussian filter. The image is effectively blurred by this convolution technique which is shown in eqn 3.2 and 3.3.

$$I_{guass}(x, y) = (Im(x, y) * G(x, y)) * G(x, y) \qquad (3.2)$$

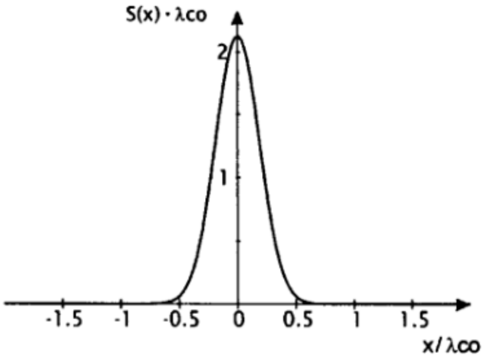
Where, Im and G(x,y) is original image and Gaussian filter kernel

$$G(x, y) = \frac{1}{2\Pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \qquad (3.3)$$

σ stands for standard deviation(σ=0.5), of the Gaussian distribution and represents the position of pixels in Gaussian window.

By using two successive convolutions with separate Gaussian kernels, the double Gaussian filter expands on the idea of the Gaussian filter. This strategy enables more sophisticated and powerful picture filtering abilities. While the second Gaussian filter boosts particular visual features or retrieves pertinent information, the first Gaussian filter is often used to remove noise and smooth the image. Utilizing double

Gaussian filters has a number of benefits, one of which is the improvement in control over the filtering outcome. The response of the filter can be tailored to varied image properties and desired results by varying the parameters of the two Gaussian kernels, such as the standard deviation and size. For instance, the original Gaussian filter could have a higher kernel size.The parameters for the double Gaussian filter are chosen based on the application's requirements and the features of the processed image. The amount of blurring or sharpening applied to the image depends on the Gaussian kernels' standard deviation. A larger standard deviation results in a broader smoothing effect as shown in Fig. 3.3 whereas a smaller standard deviation generates a more localized filter response, emphasizing fine features and edges.



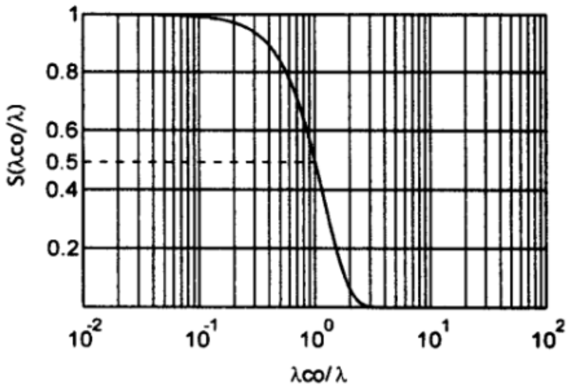


Fig 3.4 Weighted Gaussian Filter Curves[133]

The image is first convolved with the first Gaussian kernel in order to build a double Gaussian filter. The second Gaussian kernel is then convolved with the resulting image to extract the desired features or enhance the image. Convolution operations or specialized image processing libraries or software can be used to carry out the process.In texture analysis and synthesis, double Gaussian filters are frequently used. It is possible to extract and improve particular texture patterns in a picture by carefully selecting the standard deviations and widths of the Gaussian kernels. This can be helpful for tasks like material classification, object detection, and image recognition.Deblurring and restoration of blurred images is another use for double Gaussian filters. While the second Gaussian filter sharpens the image features and restores sharpness, the first Gaussian filter aids in decreasing blurring brought on by noise or motion. This method can be especially useful in situations where the blurring is uneven or varies throughout the image.

To apply a Gaussian filter in the context of input image, it is necessary to have a sufficient number of previous RSSI values [134]. Once the filtering is performed, a weight is assigned to the filtered value based on its quality to improve accuracy. If the quality value deviates significantly from 100 percent, a weight, denoted as Weight_ST, is increased. Weight_ST is determined by adding 10 for every 10 percentage points the quality value deviates from 50 percent as shown in fig. 3.3 [135]. In order to enhance the reliability of the filtered RSSI value (G_RSSI), the Double Gaussian Filter (DGF) algorithm incorporates an additional weight value. This weight is calculated by dividing the quality value by Weight_ST [136]. The Friis equation is then used to estimate the distance between the scanner and the beacon using the resultant value. The Friis transmission equation shown in eqn 3.4 describes the power received by one antenna under ideal conditions when an additional antenna transmits an established amount of power at a given distance. The received power (Pr) can be expressed in terms of the transmitting power (Pt), wavelength (λ), distance (d), and antenna gains (Gt and Gr).

$$\frac{Pr}{Pt} = GtGr\left(\frac{\lambda}{4\pi d}^{2}\right) \tag{3.4}$$

To ensure accuracy in the triangulation process, the shortest distances are used. The process of triangulating involves using the coordinates of three known points to determine the coordinates of a single point. If we know the distances between the known points and the unknown location in a two-dimensional plane, as well as their coordinates.

3.4.2 Contrast Limited Adaptive Histogram Equalization

The goal of the image enhancement method known as CLAHE is to enhance details and improve contrast in an image without overly amplifying noise or artifacts [137]. It is particularly useful for images with non-uniform lighting conditions or when there is a wide range of intensity values present. In this discussion, we will explore the concept of CLAHE, its advantages, and the mathematical equations involved in its implementation.

The process of "histogram equalization" (as shown in Fig. 3.4) is frequently used to improve an image's contrast. To produce a more consistent histogram, it redistributes an image's pixel intensities. Traditional histogram equalization, on the other hand, applies globally to the entire image, which may cause localized information to be lost and noise to be overemphasized. By segmenting the image into discrete areas and applying histogram equalization locally, CLAHE overcomes these constraints.

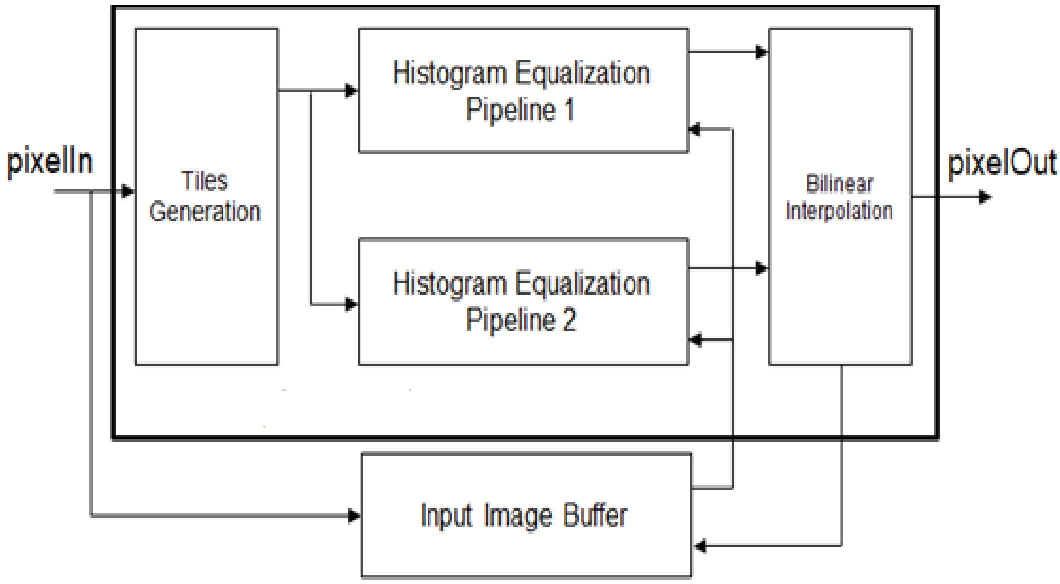


Fig 3.5 Step Wise Method for Contrast Limited Adaptive Histogram Equalization Filtering Algorithm[137]

The CLAHE algorithmworks as follows:

Algorithm 1

- **Image Partitioning:** The input image is divided into non-overlapping tiles or blocks.

- **Histogram Calculation:** A histogram is computed for each tile. The histogram represents the frequency distribution of pixel intensities within the tile.

- **Contrast Enhancement:** For each tile, a contrast enhancement function is applied to redistribute the pixel intensities. This function is derived from the cumulative distribution function (CDF) of the histogram. It stretches the histogram such that the intensities are more evenly distributed within a specified contrast limit.

  - The contrast enhancement function is derived from the cumulative distribution function (CDF) of the histogram.
  - Let H (i) represent the histogram of a tile, where i denotes the intensity value.
  - The CDF, denoted as CDF (i), is calculated by summing the histogram values up to intensity i.
  - The contrast enhancement function F(i) is defined as F(i)=NCDF(i), where N is the total number of pixels in the tile.

- **Clipping:** To avoid excessive amplification of noise, the contrast enhancement function is clipped at the contrast limit. This limits the amount of enhancement applied to each pixel.

  - After computing the contrast enhancement function, it is clipped at a specified contrast limit, denoted as L.
  - If f (i)>L, the contrast enhancement function is adjusted to L.
  - This clipping operation ensures that the enhancement applied to each pixel does not exceed the specified contrast limit.

- **Interpolation:** In order to avoid abrupt transitions at tile boundaries, neighboring tiles contribute to the enhancement process through interpolation. This ensures a smooth transition of contrast enhancement across adjacent regions.

- **Image Reconstruction:** The enhanced tiles are combined to reconstruct the final output image.

CLAHE is a potent method for boosting visual contrast while retaining local details. It has uses in a number of industries, including computer vision, satellite imaging, and medical imaging. The algorithm is a flexible tool for image enhancement because of its adaptability and capacity to regulate the contrast limit.

3.4.3 Median Filter

A common method of smoothing and reducing noise in photographs is the median filter[138]. It works very well at maintaining edges and small details while reducing inconsistencies. The Median Filter is a critical component in increasing image appearance and facilitating analysis in the context of CT (Computerized Tomography) images, where noise can reduce image quality and impact diagnostic accuracy. The idea of the Median Filter, its benefits, and the algorithmic stages, including the mathematical formulae, will all be covered in this talk. Median Filter is applied as shown in eqn. 3.5.

$$I_{med}(u, v) = med(I(u + k, v + l) \mid (k, l) \in R) \tag{3.5}$$

In this case, u and v denote the positions of the pixels in the image, k and l the positions of the pixels in the median filter window, and R the radius of the median filter window. The suggested technique performs better for R=1, or the 3x3 window.

The algorithm for a median filter

The Median Filter technique uses a simple process to even out the surface texture and minimize anomalies in CT images. These are the steps involved:

Algorithm 2

- Specify the neighborhood size: Choose the dimensions of the neighborhood window or kernel that will be applied to each picture pixel. The area surrounding the pixel of interest is known as the neighborhood, and it is often a square or rectangular area.

- Explore the picture: Apply the Median Filter operation iteratively, iterating across each pixel in the image.
- Create the neighborhood by extracting the pixel values from the defined window that surrounds each pixel in turn.
- Sort the community: Sort the neighborhood's pixel values in ascending order.
- Choosing the median value from the sorted pixel values, determine the median value. When the neighborhood size is odd, the median value is the center pixel value; otherwise, it is the average of the two central values.
- Replace the pixel value: Substitute the computed median value for the original pixel value. By using the median value, this step smooth the texture and lessens the impact of excessive or noisy pixel values.

The median value within the neighborhood is determined using the Median Filter method using a statistical approach. However, by applying the subsequent steps, we can mathematically explain the procedure:

1. Neighborhood Formation:

Let *I* represent the input image, and x,y denote the coordinates of the pixel of interest. Define a neighborhood window centered around the pixel (x,y) with a size of N×N. The neighborhood region is represented as shown in eqn. 3.6.

$$\mathrm{R} = \{\, \mathrm{I(i,j)} \mid \mathrm{x} - 2\mathrm{N} \leq \mathrm{i} \leq \mathrm{x} + 2\mathrm{N},\ \mathrm{y} - 2\mathrm{N} \leq \mathrm{j} \leq \mathrm{y} + 2\mathrm{N} \,\} \qquad (3.6)$$

2. Sorting:

Sort the pixel values within the neighborhood R in ascending order, denoted as S as shown in eqn. 3.7.

$$\mathrm{S} = \{\mathrm{I1}, \mathrm{I2}, \mathrm{I3}, \ldots, \mathrm{IN} \times \mathrm{N}\} \qquad (3.7)$$

3. Median Value Calculation:

Determine the median value, denoted as M, based on the sorted pixel values.

If the size of the neighborhood N×N is odd, the median value is given by eqn. 3.8

$$M = I\frac{NxN+1}{2} \tag{3.8}$$

If the size of the neighborhood N×N is even, the median value is the average of the two central values.

3.4.4 Mean Fusion

The final enhanced image is produced by combining the edge-smoothed image with the contrast- and texture-improved image as shown in eqn. 3.9.

$$I_{enhance} = \left(\frac{I_{gauss} + I_{med}}{2}\right) \tag{3.9}$$

Where $I_{enhance}$ is the enhanced image which is used for segmentation.

3.5 Parameters Selected For Proposed Pre Processing Method

In order to achieve best results, experiments were conducted by using different values of hyper parameters. Following section presents the values of hyper parameters which produced the best output for proposed preprocessing method.

- Gaussian Filtering:
  - Window size= 3x3 pixel
  - б=0.5
  - Two stage Guassian Filter applied in series
- Median Filtering:
  - Window size= 3x3 pixel
- CLAHE:
  - 8x8 pixel tile
  - ClipLimit = 40

3.6Pre-processing Evaluation Metrics

Several pre-processing evaluation metrics can be employed to rate the quality of the treated images when assessing the effectiveness of DSGFTCE. These measures enable quantification of the filter's efficiency in boosting texture and contrast while reducing noise. The following are some typical metrics for preliminary processing evaluation:

3.6.1. Mean Squared Error (MSE)

MSE is the average squared difference between processed image and a reference (ground truth) image as shown in eqn. 3.10.Lower MSE values indicate better image quality[139].

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - N(i,j)]^2 \quad (3.10)$$

3.6.2. Peak Signal-to-Noise Ratio (PSNR)

PSNR is logarithmic measure of the ratio between the maximum possible power of a signal and the power of noise as shown in eqn. 3.11.Higher PSNR correspond to better image quality [139][140].

$$PSNR = 10.log_{10}\left(\frac{2^B - 1}{MSE}\right) \quad (3.11)$$

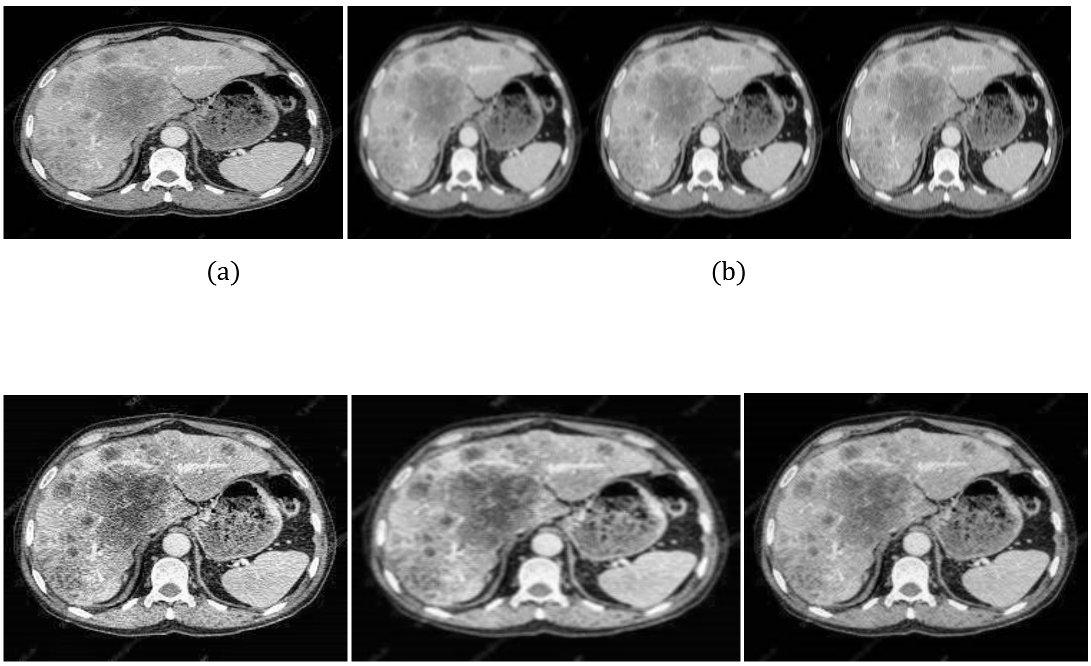
3.6.3. Structural Similarity Index (SSIM):

SSIM assesses the perceived quality of an image by measuring the similarity of its structure to a reference image as shown in eqn. 3.12.Possible SSIM values range between 0.0 to 1.0, with higher values indicating better structural similarity[140].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (3.12)$$

d. Experimental Output for Pre processing

Fig. 3.5 below shows the experimental output that is generated after applying each filter. Fig. 3.5a is the orignal CT image that is having noise. On this image Guassian filter is applied twice in series to smooth out the edges. Fig. 3.5b shows the result of applying double stage guassian filter on orignal image. Then contrast limited adaptive histogram is applied to normalize the texture and brightness of image. Fig. 3.5c shows the image after applying CLAHE. Finally median filter is applied on image to remove any salt and pepper noise as shown in Fig. 3.5 d. Finally Fig. 3.5e shows the pre processed or enhanced image.



(a) (b)

(c) (d) (e)

Fig.3.6 a) Original CT Image b) Guassian Filtered Image c) Histogram Equalization Applied Image d) Median filter Applied Image e) Enhanced image

3.7 Segmentation

The chances of patient’s survival are significantly improved by early detection [141]. For the diagnosis of liver cancer, medical imaging techniques such as computed tomography (CT) are frequently utilized [142][143]. However, the complexity and intensity differences in these images make manual interpretation and analysis difficult [144]. Segmentation techniques are used to precisely identify the liver and tumor regions in order to get over these restrictions[145]. We will look at a few segmentation techniques for detecting liver cancer in this part. Fig. 3.6 shows various steps involved in segmentation.

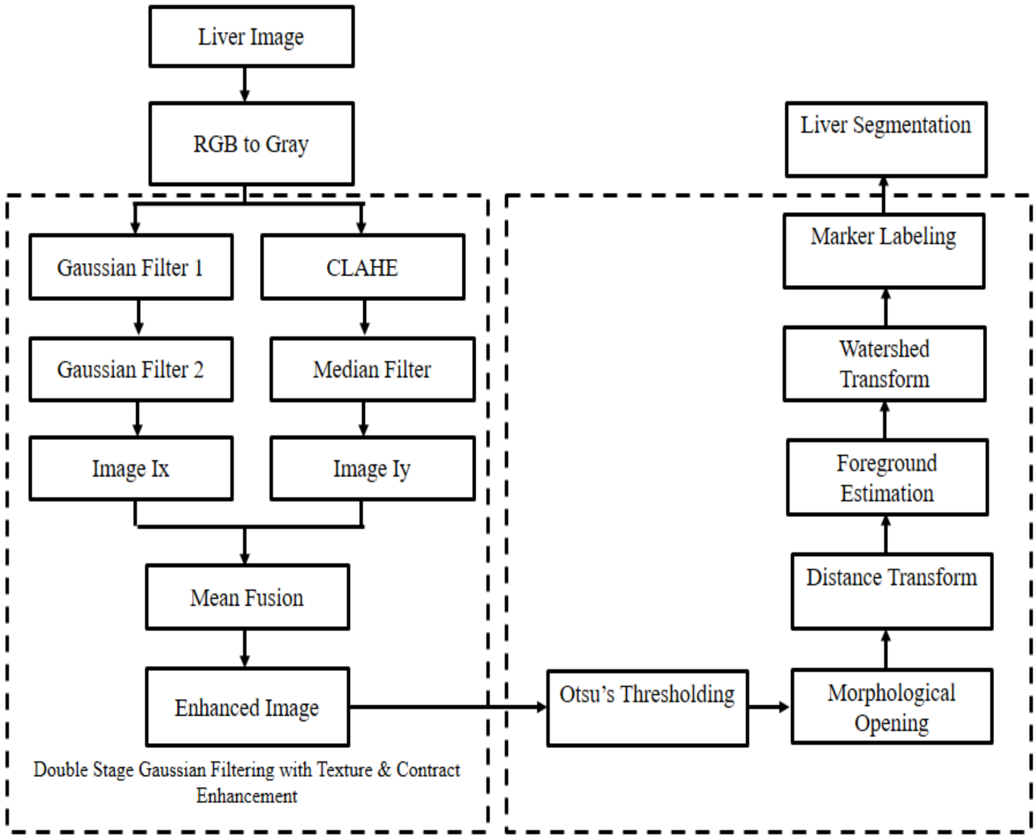


Fig 3.7 Proposed System Architecture for Preprocessing and Segmentation ofLiverimages

Need of Segmentation

In order to accurately identify and characterize tumours within medical pictures, segmentation is a vital technique employed in the detection of liver cancer [146] [147]. Increasing the chances of having an effective course of therapy and improving patient outcomes require early detection of liver cancer [148].When discussing the process of dividing medical images, such as CT or MRI scans, into different regions of interest, the term "segmentation" is used to describe the process of detecting liver cancer. These areas correspond to the many structural components of the liver, such as blood arteries, tumours, and healthy liver tissue[149].

Segmentation is employed in the identification of liver cancer for a number of reasons, including:

1. **Localization of Tumours:** Segmentation enables accurate localization of liver tumours. Clinicians can precisely locate the tumour and examine its closeness to

important structures like blood arteries or bile ducts by removing the tumourfrom the surrounding healthy tissue. Planning surgical interventions or other targeted therapies requires the use of this knowledge [150].

2. **Tumour Volume Measurement:** For treatment planning, tracking tumour growth, and assessing therapy effectiveness, accurate tumour volume measurement is crucial. By defining the boundaries of the tumour, segmentation offers a trustworthy way for estimating the tumor's size. This information helps in identifying the cancer's stage, choosing the best course of action, and monitoring therapy effectiveness over time [151].

3. **Treatment Planning:** For patients with liver cancer, segmentation is essential for treatment planning. Clinicians can simulate several therapy scenarios and assess their potential results by precisely locating the tumour location. Planning procedures like radiofrequency ablation, trans arterial chemoembolization (TACE), or radiation therapy falls under this category. Segmentation aids in reducing harm to good liver tissue when these procedures are performed [132][135] [137][152].

4. Segmentation is a critical stage in computer-aided diagnostic (CAD) systems for liver cancer. These technologies analyze medical images and help radiologists find and diagnose tumours by using artificial intelligence and machine learning techniques. These technologies can precisely segment the liver and tumours in order to automatically extract pertinent aspects and categorize suspected malignancies, offering medical practitioners helpful decision support[153].

5. After therapy, routine follow-up monitoring is essential to gauge treatment effectiveness and identify any potential tumour recurrence. By comparing subsequent scans over time using segmentation, doctors can precisely gauge changes in tumour size, shape, or appearance. This information is essential for modifying treatment plans, assessing therapy success, and spotting any indications of metastasis or recurrence of the tumour [155].

In order to identify and treat liver cancer, segmentation is a crucial approach. Planning, monitoring, and evaluation of the course of treatment are made easier by the extensive information it offers regarding tumour localization, size, and shape. Clinicians can make educated decisions and give patients with liver cancer individualized care by precisely segmenting tumours from medical pictures. The development of computer-aided diagnosis tools emphasizes the value of segmentation even more because it makes automated analysis possible and helps radiologists identify and characterize liver tumours. Early detection, precise diagnosis, and efficient treatment of liver cancer can be accomplished by the use of segmentation techniques into clinical practice, ultimately increasing patient outcomes and survival rates, the different techniques used for segmentation as shown in figure 3.7.

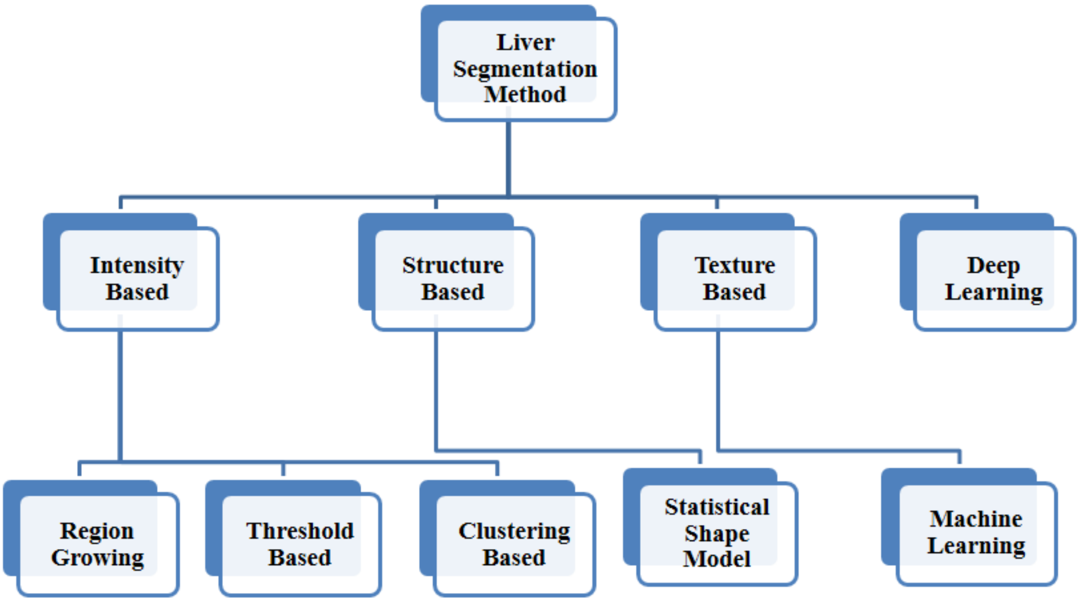


Fig 3.8 Flow Chart Showing Different Segmentation Techniques [156]

3.7.1 Intensity Based Segmentation

A popular method for detecting liver cancer in medical imaging, CTand MRI images, is intensity-based segmentation. Utilizing the differential in intensity values between tumours and the surrounding healthy liver tissue, this method helps to define and pinpoint malignant areas. An essential part of automating detection is the use of intensity-based segmentation algorithms, which also help doctors, make accurate diagnoses and design effective treatments.The basic idea behind intensity-based segmentation is to divide an image in areas according to the pixel intensity values [157]. The aim of the analysis of intensity features in the context of liver cancer detection is to discriminate between the tumour regions and the normal liver tissue.

1) Region Growing

An iterative technique called region expanding starts with a seed point or region and subsequently enlarges the region by integrating nearby pixels that meet a predetermined requirement [158]. When detecting liver cancer, the algorithm starts at a seed point inside the tumour zone and expands it by adding nearby pixels with comparable intensity properties [159]. The intensity similarity, gradient values, or other regional factors may serve as the basis for the growth criterion [160]. When there is a clear intensity contrast between the tumour site and the surrounding healthy liver tissue, region growth is especially helpful.

2) Threshold Based

Thresholding is a straightforward and often used technique in which the intensity values of the image pixels are subjected to a fixed threshold value. Tumour regions are identified by pixels with intensities above the threshold, whereas healthy liver tissue is identified by pixels with values below the threshold [161]. Several methods, including global thresholding, adaptive thresholding, and multiple thresholds based on picture statistics, can be used to conduct thresholding. The properties of the image and the required level of accuracy will determine which thresholding approach is used.

3) Clustering Based

A well-liked unsupervised clustering approach called fuzzy C-means (FCM) clustering divides pixels into groups based on how similar they are. FCM clustering can be used to divide the image into clusters that reflect tumour regions and healthy liver tissue in the identification of liver cancer. The method determines the membership of each pixel in various clusters by taking into account both the intensity values and geographical information [162]. When the intensity values of tumours and healthy liver tissue overlap, FCM clustering is helpful because it enables a more accurate depiction of the various tissue types.

4) Watershed Transform

The watershed transform is a powerful technique for segmenting objects based on regional minima and maxima in an image. It treats the intensity gradient as a topographic relief and simulates the flooding of basins to partition the image. In liver cancer detection, the watershed transform can be used to segment tumors by considering the intensity minima within the tumor region as the seed points for the flooding process[159][163]. The resulting watershed regions correspond to the tumor boundaries. However, the watershed transform can be sensitive to noise and may over-segment the image, requiring post-processing steps to refine the segmentation results [164].

The parameters of the medical image, the size and shape of the tumour, and the desired level of automation all play a role in the choice of intensity-based segmentation technique. To improve segmentation results, a mix of these techniques may occasionally be used. Furthermore, post-processing techniques like morphological operations or spatial regularization are frequently used to polish the segmentation and get rid of erroneous results[165].

Intensity-based segmentation methods provide various benefits for finding liver cancer. They first offer a quantifiable, repeatable method for locating tumour locations based on measurable standards, lowering inter-observer variability. Second, because these methods are automatable, they may be used to efficiently analyze huge datasets and support the detection and diagnosis of liver cancer [166]. Thirdly, because it offers exact details regarding tumour volume, location, and shape, intensity-based segmentation is a useful tool for treatment planning and monitoring.However, categorization based on intensity has its own constraints. The precision of segmentation can be impacted by changes in image acquisition procedures, picture, and the existence of other liver disorders. For intensity-based techniques, tumours with low contrast or infiltrative growth patterns may provide difficulties.

3.7.2 Structure Based Segmentation

A technique for detecting liver cancer that accurately identifies and delineates tumours focuses on the anatomical structures within the liver is known as "structure-based segmentation." In order to increase the precision of tumour segmentation and the efficacy of diagnostic and treatment planning, this method makes use of knowledge of the variances in liver anatomy. We shall examine the idea of structure-based segmentation for liver cancer diagnosis in this article and go over its benefits and applications.

Blood vessels, bile ducts, and distinct liver lobes are just a few of the intricate anatomical features of the liver. These structures display specific traits and connections that can be used in segmentation algorithms to distinguish between tumour and healthy liver tissue. Typical steps in structure-based segmentation approaches are as follows:

1) Statistical Shape Model

The first step in structure-based segmentation is to accurately segment the liver from medical images such as CT or MRI scans. This initial segmentation is essential as it serves as the foundation for subsequent tumor segmentation [167]. Various algorithms and techniques, including region-growing, graph cuts, and level sets, can be employed to extract the liver region based on intensity, texture, and shape information.

2) Vessel and Duct Segmentation

Blood vessels and bile ducts are key anatomical structures within the liver that can aid in tumor segmentation. Segmentation algorithms are utilized to identify and extract these structures from the liver volume. Vessel enhancement techniques and vessel tracking algorithms are often employed to extract blood vessels, while methods like region-growing and graph cuts can be used for bile duct segmentation. The extracted vessel and duct regions can be further refined and used as references for tumor localization.

Structure-based segmentation offers several advantages in liver cancer detection:

- **Accurate Localization:** By leveraging the knowledge of liver anatomy, structure-based segmentation enables precise localization of tumors within the liver. This information is crucial for treatment planning, as it allows medical professionals to assess the proximity of tumors to critical structures and plan interventions accordingly [145][152][168].
- **Improved Segmentation Accuracy:** Incorporating anatomical structures into the segmentation process improves the accuracy of tumor delineation. By considering the relationships between tumors and adjacent structures, the segmentation algorithms can better differentiate between tumors and normal liver tissue, reducing false positives and false negatives [169].
- **Enhanced Treatment Planning:** Accurate tumor localization provided by structure-based segmentation assists in treatment planning for liver cancer patients. It enables clinicians to determine the feasibility and effectiveness of different treatment modalities such as surgery, radiation therapy, or targeted therapies. Precise information about tumor size and location helps minimize damage to healthy liver tissue during interventions [74][108][170].
- **Personalized Medicine:** Structure-based segmentation facilitates personalized medicine by providing detailed information about the tumor's spatial characteristics. This information can be used to tailor treatment strategies for individual patients, considering factors such as tumor location, size, and relationship to adjacent structures.
- **Computer-Aided Diagnosis:** Structure-based segmentation is instrumental in computer-aided diagnosis systems for liver cancer. These systems utilize machine learning algorithms to analyze medical images and aid in the detection and characterization of tumors. By incorporating anatomical information into the segmentation process, these systems can improve the accuracy and reliability of tumor detection and diagnosis[171].

- The applications of structure-based segmentation extend beyond liver cancer detection. The same principles can be applied to other abdominal organs, such as the pancreas or kidneys, where the anatomical structures play a significant role in the accurate identification and delineation of tumors.

3.7.3 Texture Based

Texture-based segmentation is an effective method for improving the precision and dependability of tumour identification in medical imaging, which is employed in the detection of liver cancer. The spatial arrangement of pixels and the changes in intensity or color patterns are referred to as an image's texture. Clinicians can distinguish between various tissue types, including tumours and healthy liver tissue, by examining the textural features seen in liver pictures [172]. This paper investigates the significance, benefits, and uses of texture-based segmentation in the identification of liver cancer.

The distinctive textural characteristics of liver tumours, such as their uneven shape, varied internal structure, and distinctive texture patterns, are taken advantage of via texture-based segmentation. Because of these properties, tumours can frequently be distinguished from healthy liver tissue, making texture analysis an important tool for locating and defining tumour locations. The following are some main explanations for why texture-based segmentation is popular in the identification of liver cancer:

1) Machine Learning

The identification of liver cancer has shown significant promise thanks to machine learning-based segmentation algorithms, which offer precise and effective ways to recognize and delineate tumours within medical pictures[173]. For patients to have better outcomes and have a higher chance of receiving successful treatment, early and accurate diagnosis of liver tumours is essential. The field of medical imaging and diagnostics has been completely transformed by the successful use of AI algorithms, in particular deep learning techniques, to the segmentation of liver cancer.

Traditional segmentation techniques frequently rely on labor-intensive, subjective manual or semi-automatic processes that are sensitive to both inter- and intra-observer variability. Machine learning techniques, in contrast, use the power of artificial intelligence to automatically uncover intricate patterns and features from training data, enabling the development of reliable and effective segmentation models. Key elements of machine learning segmentation for detecting liver cancer include the following:

1. **Training Data**: To learn the patterns and traits of liver tumors, machine learning models need a lot of labeled training data [174]. For liver cancer segmentation, this typically involves annotated medical images, such as CT or MRI scans, where the tumor regions are manually delineated by experts. The performance and capacity for generalization of the machine learning model are significantly influenced by the caliber and variety of the training data.
2. **Deep Learning Architectures**: Because deep learning, a branch of machine learning, can automatically learn hierarchical representations from raw input data, it has drawn a lot of interest in the field of medical image segmentation. Convolutional neural networks (CNNs), a popular class of deep learning models, have shown incredible performance in a range of computer vision tasks, including medical image segmentation [175]. Architectures such as U-Net, Fully Convolutional Networks (FCNs), and DeepLab have been extensively used for liver cancer segmentation, effectively capturing both local and global contextual information.
3. **Preprocessing and Data Augmentation**: Preprocessing techniques are often applied to medical images before feeding them into the segmentation models. This may involve standardization, intensity normalization and noise reduction. Additionally, data augmentation methods, such as rotation, scaling, flipping, and elastic deformations, are employed to increase the variability of the training data and improve the model's generalization ability [176].
4. **Loss Functions and Optimization**: To train the segmentation models, appropriate loss functions are selected to measure the discrepancy between the predicted tumor segmentation and the ground truth annotations. Commonly used loss functions for segmentation include dice loss, cross-entropy loss, and focal

loss. Stochastic gradient descent (SGD) or its variants, Adam or RMSprop, are used in the optimization of the models to update the parameters iteratively and minimize the loss function[177].

5. **Transfer Learning and Ensemble Methods**: Transfer learning techniques are widely used in medical image segmentation to leverage pre-trained models on large-scale datasets, such as ImageNet, and adapt them to the task of liver cancer segmentation. By initializing the model with learned representations from pre-training, the need for extensive training on limited medical image data is reduced, improving segmentation performance [178]. Ensemble methods, which combine predictions from multiple models, have also been employed to boost segmentation accuracy and enhance model robustness.

6. **Post-processing and Evaluation**: After obtaining the tumor segmentation maps from the model, post-processing steps are often applied to refine the results. These may involve morphological operations, such as erosion or dilation, connected component analysis, or region-growing techniques to eliminate false positives and improve the segmentation quality. The segmentation results are then evaluated using various metrics, including dice similarity coefficient (DSC), sensitivity, specificity, and precision, to quantify the agreement between the predicted segmentations and the ground truth annotations.

Techniques for segmenting data using machine learning provide various benefits for finding liver cancer. First, they enable radiologists to concentrate on other crucial activities by reducing the physical effort and time needed for tumour delineation. Second, these techniques offer reliable tumour characterization by minimizing inter- and intra-observer variability and producing results that are consistent and reproducible. Additionally, machine learning algorithms are able to recognize subtle or heterogeneous tumour regions that manual segmentation could miss since they can acquire intricate patterns and features from a huge amount of training data.However, there are drawbacks to using machine learning segmentation to find liver cancer. The construction of precise and reliable models is frequently hampered by the scarcity of annotated medical pictures for training, particularly for uncommon or particular instances. Deep learning models' interpretability and explainability continue to be issues since they frequently operate as "black boxes," making it difficult to comprehend the reasoning behind the predictions they make. Additionally, the use and integration of machine learning models into clinical practice necessitate careful consideration of elements including computing resources, data protection, regulatory compliance, and the interaction between medical specialists and machine learning experts.

3.7.4Deep Learning

Deep learning segmentation has become a potent method for detecting liver cancer that offers many advantages over conventional segmentation techniques. Deep learning models have shown amazing accuracy in segmenting liver tumours from CT or MRI scans, by utilizing the capabilities of neural networks. In this conversation, we'll examine the tenets and advantages of deep learning segmentation for detecting liver cancer."Deep learning" is a subset of machine learning algorithms inspired by the composition and functions of the human brain. Deep learning models use artificial neural networks, which are composed of multiple layers of interconnected nodes (neurons) to extract meaningful representations from input data [179].

Deep learning segmentation's capacity to automatically pick up on and adjust to image attributes is one of its main benefits. Traditional segmentation techniques sometimes rely on hand-crafted features or heuristics, which can have limitations when it comes to handling fluctuations in tumour characteristics and image appearance. On the other hand, deep learning models have the ability to learn directly from the raw pixel data, allowing them to pick up on minute details and minute variations that might be symptomatic of liver tumours.

For image segmentation, convolutional neural networks (CNNs) are a well-liked type of deep learning models. Convolutional, pooling, and fully linked layers are among the many layers that make up CNNs.Convolutional layers apply convolution operations to learn local patterns and features, whereas pooling layers down sample the learnt features to condense their spatial dimensions. The retrieved features are then combined by the fully connected layers to produce predictions.

In the context of liver cancer detection, deep learning segmentation techniques typically involve the following steps:

1. **Dataset Preparation**: Annotated medical image datasets are crucial for training deep learning models. These datasets consist of medical images with corresponding pixel-level annotations, where the tumor regions are delineated by experts [180]. Building such datasets requires significant effort and expertise to ensure accurate and reliable annotations.

2. **Network Architecture Design**: The choice of network architecture is critical for achieving accurate liver tumor segmentation. Various architectures, such as U-Net, DeepLab, or Mask R-CNN, have been employed for liver cancer segmentation. These architectures are designed to capture both local and global information, enabling precise tumor delineation [181].

3. **Model Training**: The deep learning model gains the ability to map input images to the appropriate tumor segmentations during the training phase. In this procedure, an objective function, like dice coefficient loss or cross-entropy loss, is used to optimize the model's parameters [145][155]. Usually, gradient-based optimization algorithms like Adam or stochastic gradient descent (SGD) are used for the training.

4. **Data Augmentation**: Methods for augmenting data are often utilized to enhance the model's resilience and expandability. Using these methods, random transformations like rotations, translations, scaling, and flipping are applied to the training images. Data augmentation allows the model perform better on unseen data and learn to deal with variations in image appearance [162].

5. **Inference and Post-processing**: Once the deep learning model is trained, it can be applied to unseen medical images for liver tumor segmentation. The model processes the input image and produces a pixel-level segmentation map, where each pixel is classified as tumor or non-tumor. Post-processing techniques, such as morphological operations or region growing, may be employed to refine the segmentation map and remove potential artifacts.

Deep learning segmentation for liver cancer detection offers several advantages:

1. **Accuracy**: Deep learning models have demonstrated superior accuracy in liver tumor segmentation compared to traditional methods. Their ability to learn complex patterns and adapt to variations in image appearance allows them to capture subtle tumor features and delineate tumor boundaries with high precision [120][124][160].

2. **Automation**: Deep learning segmentation reduces the reliance on manual interventions, as the models can automatically segment liver tumors from medical images. This automation speeds up the analysis process and reduces the workload of medical professionals, enabling them to focus on other critical tasks [172].

3. **Generalization**: Deep learning models trained on large and diverse datasets can generalize well to unseen data. They can handle variations in image quality, acquisition protocols, and tumor characteristics, making them robust in real-world clinical settings [152].

4. **Efficiency**: Deep learning segmentation can significantly reduce the time and effort required for liver tumor detection. Traditional manual segmentation can be time-consuming and subjective, whereas deep learning models can process images rapidly and consistently, facilitating timely diagnosis and treatment planning [160].

5. **Integration with Clinical Workflows**: Deep learning segmentation models can be seamlessly integrated into clinical workflows and computer-aided diagnosis systems. They can assist radiologists in detecting and characterizing liver tumors, providing valuable decision support and improving diagnostic accuracy [182].

Despite its advantages, deep learning segmentation also faces certain challenges. The availability of high-quality annotated datasets is crucial for training accurate models. Generating such datasets requires extensive expertise and resources. Furthermore, deep learning models can be computationally demanding, requiring powerful hardware and substantial training time. Model interpretability and the potential for false positives or false negatives are also areas of ongoing research and development.

3.8 Feature Extraction

Feature extraction is the process of identifying certain characteristics in medical images which can be used as a conclusive evidence to classify a given image into a particular output class. For example in case of cancer detection through machine learning algorithm, feature extraction can be done as a preprocess step to help classify a given image into normal or cancer image. Feature extraction is only required in case of machine leaning algorithms.

Deep learning algorithms does not require feature extraction as a separate step, as it is the specialty of deep learning algorithms that it tries to learn the features from the input data themselves, whereas in machine learning algorithms feature extraction techniques must be applied before classification. Proposed technique is based on deep learning but in order to compare the performance of proposed method with other machine learning algorithms, we are implementing above mentioned machine learning algorithms on our data set under same environment. For this reason we are discussing feature extraction techniques in below section.

There are various types of feature that can be generated for classification and there are also various methods to extract these features from the given image. Fig3.8 gives an idea of various types of features that are extracted to classify an image into normal or cancerous image.

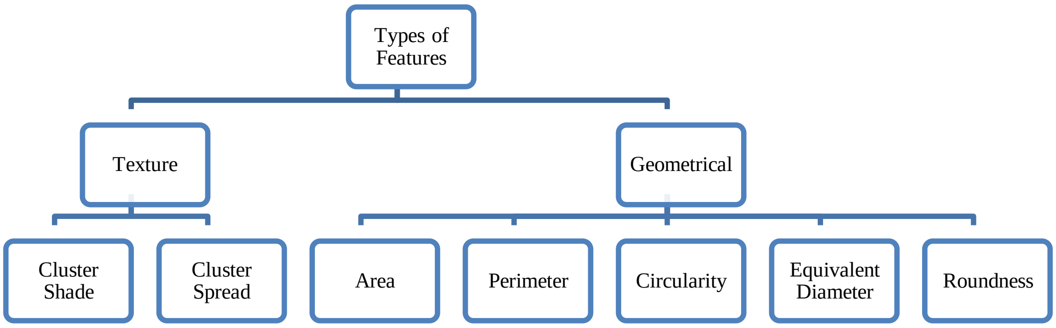


Fig 3.9 Types of Features Extracted for Proposed Work

Various algorithms and methods are available which can be utilized to extract above mentioned features from the medical images, few of which are mentioned below.

1. Intensity Histogram

This feature displays the frequency at which each pixel's intensity value appears again in the picture [162]. As a result, this feature does not consider the locations of the pixels within the image; instead, it depends only on the number of pixel intensity repetitions.

2. Histogram of Oriented Gradients (HOG)

There are cell divisions in the image. Next, the gradient's orientation within every cell is calculated. Lastly, each gradient orientation is counted, and the counts are used to create a histogram. [163].

3. Gabor Filter

It is a specialized linear filter particularly utilized for texture analysis. In this technique, the image’s specific frequency content is analyzed in guided directions in localized region to analyze textural difference.

4. Proposed Method for Feature Extraction

A novel method is proposed to identify cancer cells based on the features extracted using a combination of colourpalleting and HAAR cascading to find abnormality in the given image. Fig. 3.9 presents the various steps involved in feature extraction process.

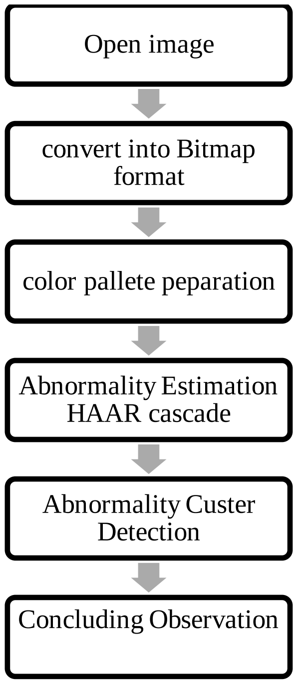


Fig 3.10 Flow chart of proposed feature extraction method

In the first step a raw image is converted into bitmap file. In the second step colour palette is prepared to find out various colours contrast present in the image. Any flood fill algorithm can be utilized on this image to separate various objects in an image. In final step, cascade of haarclassifier can be trained to recognize a wide range of objects, such asshapes,area, and clusters and there spread, etc. Haar cascade uses the cascading window to learn more about how it works by attempting to compute features in each window and determine whether it might be an object [184]. A Haar feature in a detection window is essentially the outcome of computations on neighboring rectangular sections. The pixel intensities in each region must first be added in order to determine the difference between the sums.

3.9 Software development Tools

The system specifications and implementation details of the liver cancer detection system are shown in Table 3.1 Implementation of the deep learning algorithms requires higher computation and has larger complexity. To implement the robust algorithm, we have selected python programming language which is robust, portable and platform independent.

Table 3.1 Implementation tools details of the liver cancer detection system

Parameters	Specifications
Implementation Environment	Windows 8.0
System Details	Personal Computer with core i5 processor, 2.64GHz speed and 8 GB RAM
Programming Language	Python
Toolboxes	Computer Vision and Image Processing Toolbox, Signal processing Toolbox, Deep Learning Toolbox
Database (Liver CT images)	LiTS dataset and Clinical Data
Editor	Spyder 4.0

3.10 Advantages of Proposed Method over Existing Techniques

Proposed method for liver cancer detection using DCNN has several advantages over exiting techniques:

1. Multi-Stage approach provides better image quality for segmentation as compared to single filter technique.
2. Modified watershed algorithm has provided better segmentation results as compared to traditional watershed algorithm as shown in results section in chapter 5.
3. Deep Learning techniques have been utilized for feature extraction and classification which automatically learns feature from images thus improving accuracy as compared to machine learning approach which rely on hand crafted feature.
4. Proposed method provides a solution for multi class cancer detection which is a very challenging job still today.
5. Proposed method uses multiple evaluation matrices at each stage(Pre-processing, Segmentation and Classification) allowing a thorough assessment of its performance.
6. Proposed method focuses on automation at each step, and aims to minimize manual intervention and it also requires very less tuning of hyper parameters.

3.11 Summary of Pre-Processing and Segmentation

Proposed preprocessing technique was successfully able to remove noise from CT images. In order to prove whether preprocessing improves the quality of segmentation or not, we applied segmentation techniques on both preprocessed and raw CT images. Experimental results proved that preprocessed images give better segmentation results. Also, segmentation technique which is based on marker controlled watershed algorithm showed significantly better results than other state of the art techniques mentioned in research articles. Results of both preprocessing and segmentation techniques are discussed in detail in chapter 5.

Chapter - 4

PROPOSED CLASSIFIER

Deep convolutional neural networks (DCNNs) have revolutionized the classification of medical images by delivering cutting-edge results across a variety of applications. Using their capacity to automatically learn complicated hierarchical features from raw pixel data, CNNs are a form of deep learning model created specifically for image analysis. We will examine the essential elements and benefits of deep CNNs for medical picture categorization in this discussion

4.1 Introduction

One of the most important benchmarks for image classification and segmentation tasks in the field of image analysis has seen the development and impressive performance of numerous CNN-based deep neural networks. The processing on image dataset Challenge is a rigorous evaluation platform for determining the capabilities of deep learning models because it uses a large-scale dataset with millions of labelled images from a variety of classes [183].In the Image dataset Challenge, a number of deep neural network architectures, including VGGNet, ResNet, InceptionNet, and Efficient Net, have made important strides [184]. These designs use sophisticated approaches to efficiently extract and learn complex features from unprocessed visual input, such as deep convolutional layers, pooling layers, and powerful regularization algorithms [185]. These networks have demonstrated their capacity to generalize and categorize images with high accuracy by training on the primary and secondary dataset [186].

Furthermore, deep neural networks have made great progress in picture segmentation tasks in addition to excelling at image classification. Segmentation is the process of pixel-by-pixel separating objects or areas of interest from the background of an image. Semantic segmentation has been particularly successful with Fully Convolutional Networks (FCNs) and U-Net architectures, which offer precise pixel-level labeling of distinct classes within an image.The successes in the ImageNet

Challenge and ensuing improvements in image segmentation and classification have had a significant influence on a variety of fields. These include applications of deep learning to medical imaging, where issues including tumour identification, organ segmentation, and illness categorization have been tackled. Research has advanced significantly due to the transfer of skills and knowledge from general image analysis to medical image analysis.

4.2 Classification Using Deep Convolution Neural Network

A convolutional neural network (CNN) is composed of three fundamental neural layers: the convolutional layer, pooling layer, and fully connected layer. Every layer contributes differently to the way the network works. Convolutional layers are used to identify various features in images, including edges and other visual elements. This is achieved by carrying out mathematical operations, such as multiplying local neighbors of each pixel by predefined kernels [187]. Specific components of the input image are highlighted in the feature maps created by these convolutions. After the convolutional layer, the pooling layer is used to reduce the spatial dimensions (width and height) of the data without altering its depth [188]. Sub sampling is a technique that helps reduce the computing demands on succeeding layers.

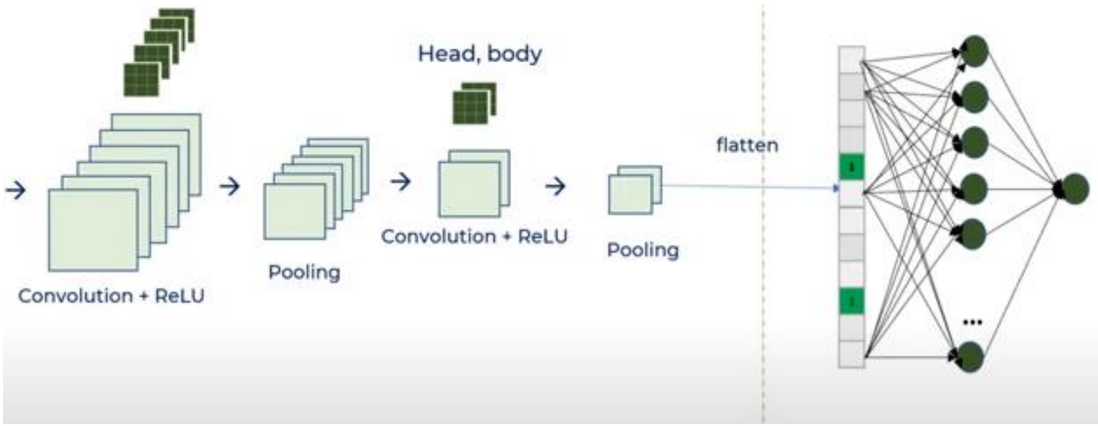


Fig 4.1 Deep Convolution Neural Network Architecture[186]

Last but not least, the fully connected layers of the neural network are in charge of high-level reasoning. Incorporating the feature responses collected from the earlier layers, these layers enable the network to make difficult decisions and generate the final outputs. Every neuron from one layer connects to every neuron in the layer below it, allowing for thorough processing and analysis of the retrieved information.CNN models with ReLU (Rectified Linear Unit) activation are frequently used for a wide range of computer vision tasks, such as object recognition, image segmentation, and image classification [189]. In this explanation, we will look at the architecture and benefits of a CNN model with ReLU activation, as illustrated in (Fig. 4.1) CNN models typically contain convolutional, pooling, and fully linked layers. The ReLU activation function is usually applied after the convolutional layers to add non-linearity and increase the expressive power of the network.

CNN models with Rectified Linear Unit (ReLU) activation are widely used for a wide range of computer vision tasks, such as object recognition, image segmentation, and image classification. In this explanation, we will look at the architecture and benefits of a CNN model with ReLUactivation.CNN models typically contain convolutional, pooling, and fully linked layers. The ReLU activation function is usually applied after the convolutional layers to add non-linearity and increase the expressive power of the network.

4.2.1Convolutional Layers

The convolutional layers in a CNN model perform the task of feature extraction. These layers apply a set of learnable filters to the input image, which perform convolutions across the image to extract local patterns and features as shown in Fig.4.2. Each filter captures different visual characteristics, such as edges, textures, or shapes.

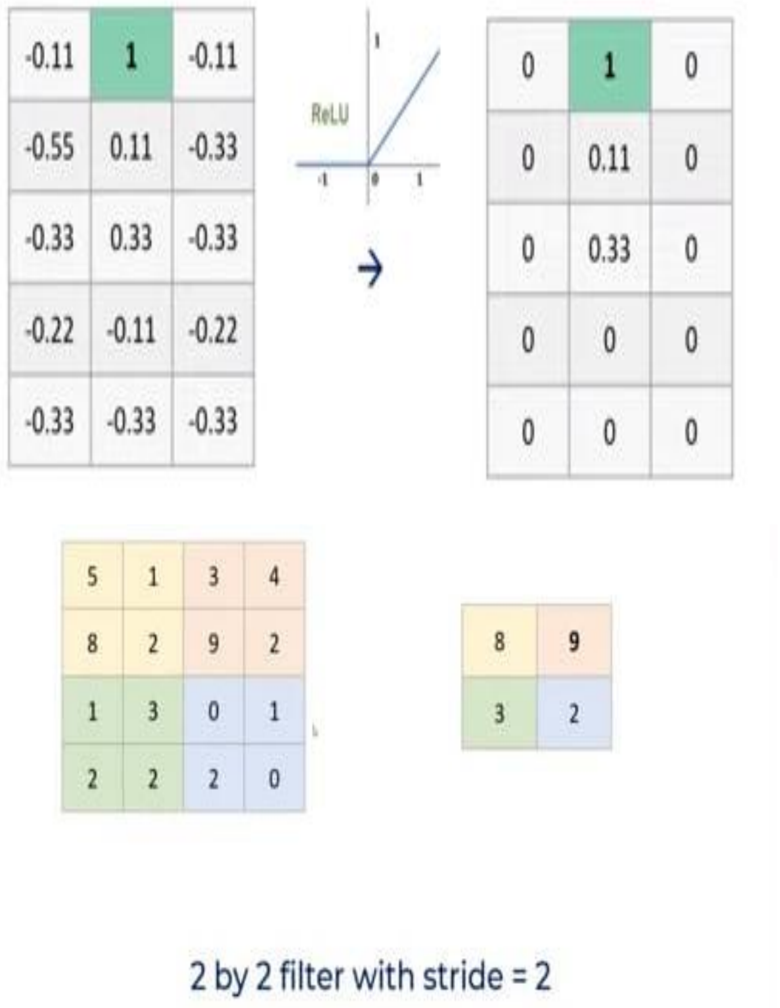


Fig 4.2 Convolution Layer for DCNN

Convolutional layers are responsible for learning increasingly complex and abstract features as the network deepens.Each pixel in an image that is being processed acts as an input for the network. Input neurons would number 120,000 if, for example, the image has dimensions of 200x200x3 (200 pixels in height, 200 pixels in width, and 3 color channels: red, green, and blue).The input matrix is depicted as a 200x200 grid of pixels in the network's first layer, with each pixel having three color values that correspond to the red, green, and blue channels. The matrix has 200 * 200 = 40,000 entries as a result. Additionally, three copies of this matrix one for each color channel are created.

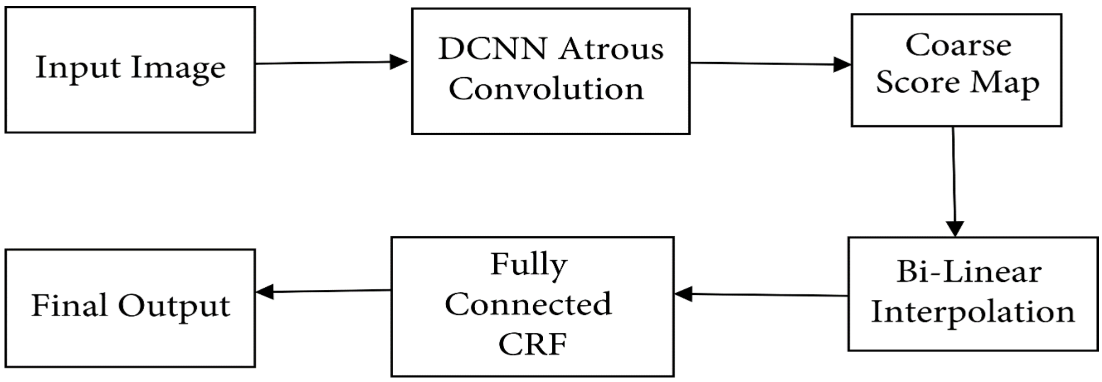


Fig 4.3 Deep Convolution Neural Network Process Flow [190]

The input image is processed in the proposed architecture using a deep CNN layer that contains one or two convolution layers (as shown in Figure 4.3).Within a CNN, the convolution layer is essential for processing images. In this layer, we define a step length that controls the gap between calculations and a filter that controls the size of the partial images. We successfully lower the image's dimensionality by doing this.The pooling layer comes next after the convolution layer. This layer helps to reduce the dimensionality of the data, just like the convolution layer does. The pooling layer functions similarly to the convolution layer in terms of computing. Nevertheless, depending on the particular application, we normally select either the average or maximum value from the findings in the pooling layer.The pooling layer's goal is to preserve significant small-scale features within a few pixels that are essential for completing the task at hand. Pooling improves computing efficiency and helps avoid over fitting by capturing the most important data while removing irrelevant features.The pooling layer provides the average pooling and maximum pooling methods. We determine the average value within a certain area of the feature map when we use average pooling. As a result, the network is more resilient to minute spatial fluctuations in the input image and noise is reduced. Max pooling, on the other hand, preserves the most salient features and highlights their significance in succeeding layers by choosing the maximum value within the defined region.

A rough feature map that captures significant visual patterns and details is produced by this approach. The feature map is then up sampled using bilinear interpolation to make sure that it is compatible with the original image size. By aligning the coarse features with the fine details included in the input, this interpolation technique raises the resolution of the feature map to match that of the original image.The interpolated data is then run through a fully connected conditional random field (CRF) layer after the up sampling step. The CRF is a probabilistic graphical model that takes into account how the pixels in an image are related to one another. The CRF improves the segmentation process' accuracy by fine-tuning the coarse feature map and utilizing the spatial correlations between nearby pixels.The final segmented image is represented by the output of the fully connected CRF layer, where each pixel is given a label relating to the particular class or category to which it belongs. The coarse features collected by the CNN layer, the up sampling of the feature map, and the fine-grained contextual data offered by the CRF layer are all combined throughout this segmentation phase.

4.2.2 Rectified Linear Unit Activation

The CNN model gains non-linearity through the use of an activation function called the Rectified Linear Unit (ReLU). It works element-by-element on each convolutional layer's output, preserving positive values and setting negative values to zero. ReLU has a mathematical definition of $f(x) = \max(0, x)$, where x is the activation function's input [191]. The network can more effectively model intricate relationships between input features thanks to the computationally efficient ReLU activation function [192].

The ReLU activation function has several advantages that contribute to its popularity:

Simplicity: The ReLU function is computationally efficient and easy to implement. It involves only a simple thresholding operation, making it faster to compute compared to other activation functions that involve more complex calculations [193].

Non-linearity: The non-linear nature of ReLU allows neural networks to learn and model complex relationships in data [194]. By introducing non-linearity, ReLU enables the network to capture and represent highly nonlinear patterns and features, making it suitable for solving complex tasks.Sparse Activation: ReLU exhibits sparsity in its activations. When the input is negative, ReLU outputs zero, effectively deactivating the corresponding neuron [195]. Due to the sparsity property, training and inference are accelerated because only a portion of the network's neurons are activated for each input, hence lowering computational complexity. Vanishing gradient mitigation [196]. Back propagation in deep networks may give rise to the vanishing gradient issue, which the ReLU activation function helps to mitigate. The term "vanishing gradient problem" describes how gradients become smaller as they move through multiple layers, which causes slower convergence and makes learning deep architectures more challenging. ReLU activations allow gradients to flow more freely and keep them from vanishing because they do not saturate in the positive region.

Algorithm: 3

Step 1: Input Layer

The input layer, where the input image or data is sent into the network, is where the algorithm begins.

Step 2: Convolution Layer

In this step, learnable filters are convolved with the input data to extract features. Each filter creates feature maps by performing a convolution operation on the input data. This step's output can be modeled as shown in eqn. 4.1:

$$FeatureMaps = Convolution(Input, Filters) \tag{4.1}$$

Step 3: Activation Function (ReLU)

The feature maps acquired from the convolution layer are then element-by-element subjected to the ReLU activation function. All negative numbers are reset to zero, while positive values are left unaltered. The ReLU activation can be characterized mathematically as shown in eqn. 4.2.

$$ReLU(x) = max(0, x) \tag{4.2}$$

Step 4: Pooling Layer

The feature maps' spatial dimensions are decreased while crucial data is preserved by the pooling layer. Maximum pooling, which chooses the highest value within a pooling window, is the most widely used pooling technique. The following can be used to represent this step's output as shown in eqn. 4.3

$$PooledFeatureMaps = MaxPooling(FeatureMaps) \qquad (4.3)$$

Step 5: Fully Connected Layer

The pooled feature maps are joined to a fully connected layer after being flattened. High-level reasoning and the mapping of the features to the appropriate output classes are carried out by the fully connected layer. The output of the completely connected layer can be modeled mathematically as shown in eqn. 4.4.

$$Output = FC(Flatten(PooledFeatureMaps)) \qquad (4.4)$$

Step 6: Softmax activation

The output of the fully connected layer is frequently subjected to a softmax activation function when the network is used for classification. The output is transformed into a probability distribution over the classes by Softmax, which enables the network to predict classes. One definition of the softmax function is shown in eqn. 4.5.

$$Softmax(xi) = \frac{e^{xi}}{\sum_{j=1}^{C} e^{x_j}} \qquad (4.5)$$

Step 7: Loss Function and Optimization

The difference between the expected output and the true labels is measured using a loss function, such as categorical cross-entropy. The network's weights and biases are then updated and the loss is minimized by applying an optimization algorithm, such as gradient descent or its variations, to the network. Until the network achieves a performance level that is deemed acceptable, these procedures are repeated several times over, or epochs.

Depending on the particular job and degree of difficulty of the problem at hand, the general design of a CNN model with ReLU activation may change. Much cutting-edge architecture, such VGGNet, ResNet, or InceptionNet, use multiple layers and additional methods to improve the speed of the model, like skip connections or inception modules.Back propagation and gradient-based optimization methods, such as stochastic gradient descent (SGD) or Adam, are used to optimize the CNN model during the training phase [198]. The network's weights and biases are adjusted by the model as it learns to minimize a specified loss function, which is commonly categorical cross-entropy for classification tasks.

4.2.3 ResNet

Convolutional Neural Networks (CNNs) were used to create the robust pre-trained deep learning model ResNet-50, which was created for image classification. CNNs are highly suited for applications like image recognition because they were created primarily for analyzing visual data [199]. As its name implies, ResNet-50 has 50 layers and was trained using a sizable dataset of one million photos from the ImageNet database, which spans 1000 different categories.ResNet-50's deep architecture, which enables it to capture complex characteristics and patterns in images, is one of its most prominent advantages [200]. The model has a great capability for learning complicated representations and has about 23 million trainable parameters. By using a pre-trained model, developers can take advantage of the thorough training carried out on large-scale datasets [201]. ResNet-50 distinguishes out among other pre-trained deep models for recognition tasks due to its superior generalization performance and lower error rates than AlexNet, GoogleNet, and VGG19 [202]. Across a range of picture classification difficulties, it has proven to have greater accuracy and durability. As a result, ResNet-50 as shown in Fig. 4.4 is a useful tool for image identification jobs since it provides a solid base for further development and fine-tuning for particular applications [203].

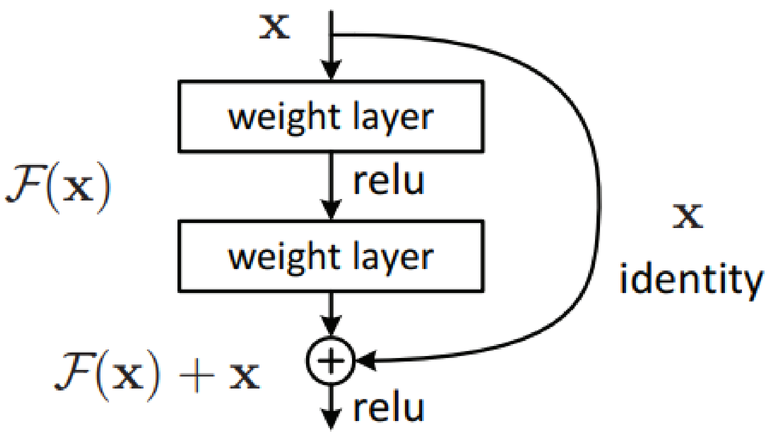


Fig 4.4 ResNet Architecture [203]

As opposed to creating a deep learning model from scratch, developers can save a lot of time and computing resources by using a pre-trained model like ResNet-50 [204]. The pre-trained model can generalize successfully to new, unobserved data since it has already acquired meaningful representations from a wide variety of images. The model's performance is further improved and is tailored by fine-tuning it for a particular dataset or task as shown in eqn. 4.6.

$$F(x) := H(x) - x which gives H(x) := F(x) + x \quad (4.6)$$

ResNet-like techniques include "highway networks," which also use skip connections. Similar to LSTM networks, these skip connections have parametric gates that control the information flow through the skip connection. The amount of data that can pass through these gates is set by them [205].Highway networks, although using these parametric gates and skip connections, have not been able to match the precision attained by the ResNet architecture. Highway networks are a different architecture for deep networks with skip connections, although they function less accurately than ResNet in terms of performance. ResNet's exceptional accuracy can be due to its distinctive architecture, which makes deep neural network training efficient. ResNet addresses the vanishing gradient issue by allowing for the direct flow of gradients during back propagation by using residual connections, where the input is appended to each layer's output. This makes it easier to train deeper networks, making it possible to extract more complicated features and improving the network's capacity to learn sophisticated representations.

4.3Basic Convolution Neural Network Operations

Convolution is a specialized linear process that is essential to deep learning models' feature extraction. It includes applying a tiny number array, referred to as a kernel or filter, across an input number array, known as a tensor. The kernel and the associated of the tensor. The output value for that place in the resulting tensor, known as a feature map, is created by adding these products.Multiple kernels are applied in parallel to the input tensor to extract various features and capture diverse properties. Each kernel can be thought of as a unique feature extractor, taking specific patterns or data from the input. As a result, various feature maps are produced, each one depicting a unique feature or facet of the input dataset.

The convolution operation is defined by two key hyperparameters as shown in Fig. 4.5. The first is the kernel's size, which is commonly stated as a dimension like 3 by 3, however bigger values like 5 by 5 or 7 by 7 can also be used. The receptive field, or the area of the input that the kernel considers at each position, is determined by the size of the kernel.

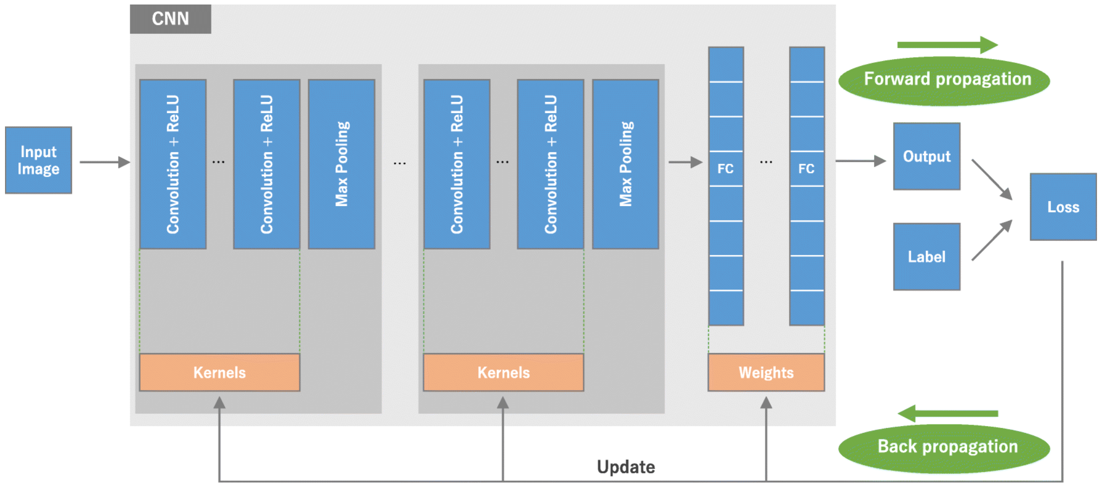


Fig 4.5 Overview of Convolutional neural network [206]

While a smaller receptive field concentrates on local details, a larger one enables the kernel to gather more global information. Convolution is a specialized linear process that is essential to deep learning models' feature extraction. It includes applying a tiny number array, referred to as a kernel or filter, across an input number array, known as a tensor. The kernel and the associated elements of the input tensor are computed as an element-wise product at each location of the tensor. The output value for that place in the resulting tensor, known as a feature map, is created by adding these products.The number of kernels used in the convolutional layer is the second hyperparameter. This parameter controls how many or how deep feature maps are output. Each kernel functions as a different feature detector, picking up on particular structures or patterns in the incoming data. The network may learn a wider range of information and take in more complicated representations by increasing the number of kernels.

4.3.1 Max Pooling

Max pooling is the most often utilized method of pooling operations in deep learning. It entails picking the highest value present in each non-overlapping area of the input feature maps and rejecting all other values shown in Fig. 4.6. Max pooling is often carried out with a stride of 2 and a filter size of 2 x 2. This process down samples the feature maps' spatial dimensions (height and breadth) by a factor of 2.The size of the pooling filter determines the non-overlapping zones into which the input feature maps are split during max pooling. The maximum value is determined for each region and kept, while all other values are deleted. This deliberate pooling of maximum values aids in identifying the most salient characteristics.

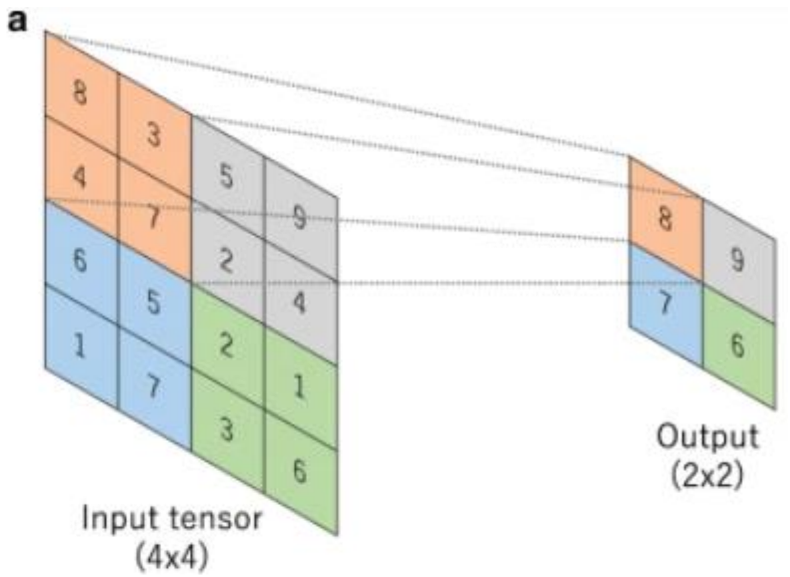


Fig 4.6 Overview of Max Pooling Mapping Matrix

The pooling zones won't overlap when a stride of two is used, preventing a downsampling impact. Due to the downsampling, the height and breadth of the feature maps are virtually cut in half. The number of feature maps or channels is represented by the depth dimension, which doesn't vary.Max pooling assists in lowering the computational demands on succeeding layers in the network by downsampling the spatial dimensions. By keeping the most relevant details while removing the less crucial ones, it reduces the dimensionality of the data. The strongest activation is represented by the maximum value within a patch, regardless of its exact location within the patch, hence this process also contributes some translation invariance.In deep learning, max pooling is a popular pooling operation. It eliminates all other values and chooses the highest value found within non-overlapping portions of the supplied feature maps. Max pooling minimizes computing complexity and aids in capturing significant features while keeping the depth dimension of the feature maps by down sampling the spatial dimensions.

4.4Classification of Medical Image

Deep learning techniques are frequently used in the field of medical image analysis for classification tasks, particularly for differentiating between different classes of target lesions shown in Fig. 4.7. Convolutional Neural Networks (CNNs), for example, are deep learning methods commonly used to classify liver nodules observed in computed tomography (CT) scans as benign or malignant [207]. Preparing a sizable amount of training data with relevant labels is necessary to enable efficient CNN classification.

The classification of target lesions in medical pictures can be done using the CNN model after it has been trained using this labeled training data [208]. In this deployment phase, the target lesions in the provided medical pictures are identified by either medical professionals or computer-aided detection (CAD) systems using the trained CNN model.

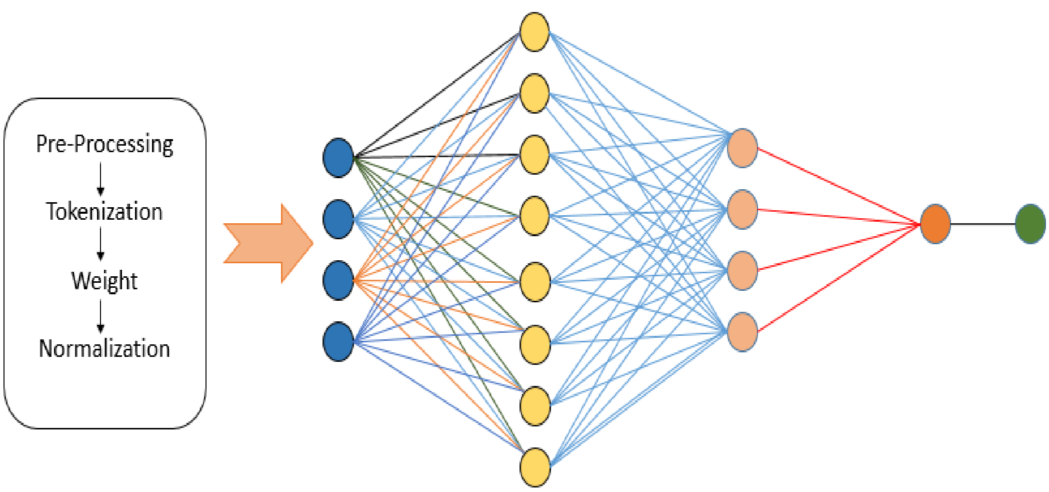


Fig 4.7 Convolution Neural Network Process Flow[210]

CNNs are widely used for early illness identification because of their accuracy in analysing and classifying complex patterns in medical images or data.

- Convolutional Layers: The CNN employs convolutional layers to extract relevant features from the input data. These layers apply filters to the input in order to convolve it and identify structures and spatial correlations as shown in eqn. 4.7.

$$Z\ (I, J) = \sum_{m,n} Y(i-m, j-n).K(m,n) \qquad (4.7)$$

  where Z (I , J) represents feature map at position (I , J), Y (i-m,j-n) is the input data at position (i-m,j-n), and K(m,n) is the kernel at position (m,n).

- Activation Function: Activation functions introduce non-linearity to the network and help it learn associations as shown in eqn. 4.8.

$$F\ (X) = \text{Maximum}\ (0\ ,\ X) \qquad (4.8)$$

  where f(x) is the output value after applying the ReLU activation to input x.

- Pooling Layers: Pooling layerreduce the dimensionality of feature map by down sampling them while retaining the most important features. The most popular pooling technique is maximum pooling, which selects the highest value within a pooling window. In mathematics, max pooling is represented as shown in eqn. 4.9

$$Y\ (i, j) = \text{maximum}\ (X\ (i, j), X(i, j)) \qquad (4.9)$$

  where, Y(i,j) represents the output of the pooling operation at position (i,j), and X(i,j) represents the input data at position (i,j).

- Fully Connected Layer: A fully connected layer is responsible for the high-level reasoning in the CNN. It joins every neuron from the previous layer to every neuron in the current layer. The output of previous layer is flattened into a 1D vector and multiplied by a weight matrix. Mathematically, the fully connected layer can be represented as shown in eqn. 4.10

$$Y = f(XW + b) \qquad (4.10)$$

Where, Y and X are output vector and input vector, W is the weight matrix, b is the bias vector, and f() is the activation function.

- In order to create a classifier, the output from the layers before it is flattened and fed into fully connected layers. These layers ascertain the relationships between the extracted data.
- The output layer of the CNN generates the predicted class probabilities. Depending on the particular goal, this classification could be multi-class (identifying several diseases) or binary (identifying healthy vs. diseased).
- The CNN is trained with labelled data in order to minimize the prediction error. Back propagation and optimization techniques, such as gradient descent, are then used to modify the network's weights and biases.
- Using different test data, the CNN's ability to identify diseases in their early stages is evaluated following training. Often, metrics like accuracy, precision, recall, and F1 score are employed to evaluate its effectiveness.
- Loss Function: The difference between the true labels and the predicted output is measured by the loss function. Cross-entropy loss and softmax loss are typical loss functions for classification tasks. The particular problem being solved determines which loss function should be used.

Deep convolutional neural networks (DCNNs), which automatically learn complex features from raw pixel input, have revolutionized the classification of medical images. They have displayed exceptional performance in tasks like picture segmentation and classification. In these domains, CNN designs like VGGNet, ResNet, InceptionNet, and EfficientNet have advanced significantly. Convolutional, pooling, and fully linked layers are the main building blocks of CNN models. While pooling layers lower the spatial dimensions of the data, convolutional layers use filters to extract information from the input image. Fully connected layers produce the ultimate outputs and carry out high-level reasoning. ReLU activation is frequently used to add non-linearity and enhance CNN models' expressiveness.It has benefits including simplicity, nonlinearity, sparse activation, and vanishing gradient problem mitigation [209]. The input layer, convolution layer, ReLU activation, pooling layer, fully connected layer, softmax activation, loss function, and optimization are all components of the CNN classification algorithm. Due to its complex architecture and reliable representations, ResNet-50, a pre-trained CNN model with 50 layers, has shown great performance in image recognition tests [210]. Pre-trained models like ResNet-50 can save time and resources, and their performance can be further enhanced by fine-tuning them for particular tasks. The ResNet architecture uses residual connections to address the vanishing gradient issue, enabling the training of deeper networks and collecting more intricate information.

4.5 Training, Testing and Validation of DCNN

Deep Neural Networks like all other classifier needs to be trained, tested and validated before they can be used to perform classification in real world. Following approach has been utilized to train and validate proposed classifier.

- Selection of proper training data. It is very important to select proper training data that is noise free, have equal frequency of all class and properly annotated. Proper data greatly increases the accuracy of classifier.

- Design of neural network architecture. This step involves finalizing the size of input layer, number of hidden layers, types of kernel, fully connected layer, activation functions and type of output layer. It also requires fine tuning various hyper parameters to achieve best results.

- Finalizing performance evaluation metrics and setting target for classification performance. This is achieved by studying the performance of various state-of-the-arts.

- We have divided the data into 70:15:15 ratios for training testing and validation. 70% of data will be used for training, 15% for testing and 15% for validation.

- Finally accuracy for all the three steps, training, testing and validation is calculated using data from confusion matrix. The process of training and testing is repeated until desired performance is not achieved.

4.6 Summary of Classification

In this chapter we have discussed in detail the architecture of proposed DCNN. In proposed approach we have used DCNN for both feature extraction and classification. In recent times most of the new techniques are based on DCNN because of their inherent ability to extract and identify features which are otherwise difficult to define or identify for naked eyes. Classification accuracy depends on proper feature extraction. If the features are extracted properly than only the classifier will be able to properly classify the image as normal or a particular type of cancer.

There are various types of hyper parameters that can tune in order to increase the classification accuracy of DCNN. Major parameters that are fine-tuned are number of convolution layers, size of kernel for convolution layer, no. of max pooling layer, size of filter for max pooling layer, stride of convolution and max pooling operation, test and training data split, optimizers and loss functions applied and finally function used for classification. These hyper parameters are presented in the form of table in chapter 5 in table number 5.3. All the layers and parameters mentioned above are discussed in this chapter inn details.

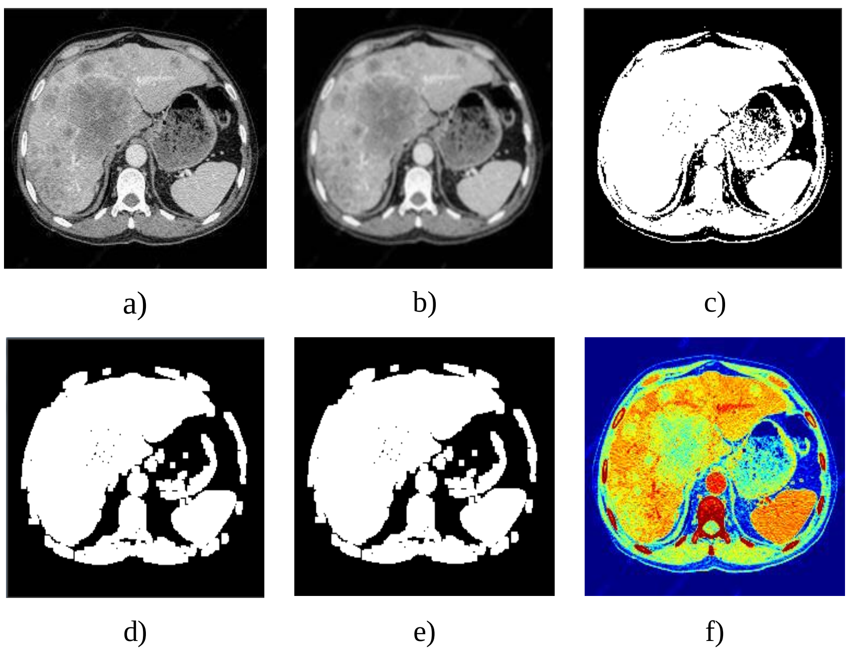
Chapter 5

RESULTS AND DISCUSSION

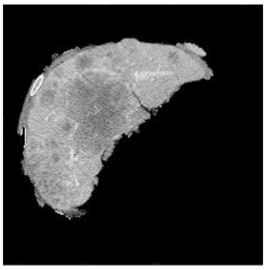
In this chapter result of proposed preprocessing, segmentation technique and classificationtechnique is discussed. We have used LiTs data set consisting of 200 liver CT images for testing proposed segmentation technique. Output in the form of images and results are shown and discussed in detail in this chapter. Primary data consisting of more than 1500 images and secondary dataset from TGCPA consisting another 1500 images were used to train test and validate DCNN architecture. Results of implementation of DCNN are shown in the form of images, tables and various types of charts in this chapter.

5.1 Preprocessing and Segmentation

The visualization of the various stages of the proposed liver segmentation is shown in Fig. 5.1.Output of various operations is shown as per the preprocessing and segmentation method discussed in chapter 4.



g)



h)

i)

Fig 5.1a) Original CT Scan Image b) Gaussian Processed Image c) Otsu'sProcessedImage d) Morphological ProcessedImage e) Distance transformed Processed Imagef) Watershed Filtered Imaged g) Watershed Marked lines h) Segmented liver area i) Segmented Region of Interest

A) Pre Processing Performance Analysis

In this section we have presented the results of proposed preprocessing technique and also compared our results with other state of the arts. Initially we have implemented median filter on LiTs dataset and compared the results of implementation with proposed method for different filter sizes. The performance of the proposed modified filtering approach is evaluated for the different filter kernel as given in table 5.1

Table 5.1 Pre Processing Performance Comparison between Guassian Filter and Proposed Method

Method	**7 x 7 Window**			**5 x 5 Window**			**3 x 3 Window**		
	PSNR	**SSIM**	**MSE**	**PSNR**	**SSIM**	**MSE**	**PSNR**	**SSIM**	**MSE**
Gaussian Filter	43.08	0.7	0.8	48.39	0.83	0.94	48.23	0.75	0.98
Proposed Filtering Approach	50.34	0.89	0.6	49.55	0.88	0.72	48.94	0.84	0.83

Next, we contrasted the suggested pre-processing method's performance with that of other cutting-edge techniques. The work of authors who pre-processed their images using the CLAHE, median, and gaussian filters is listed in the following table. These filters are employed in many different applications, and the validation of results is done using various evaluation parameters. Performance analysis and comparison of performance of proposed method is discussed in Table 5.2.

Table 5.2 Comparison of Pre Processing Performance with State-Of-The-Art

Author	Application	MSE	PSNR	SSIM
Sreejith &Nayak(2023)	Digital Image Processing	0.18	19.89	0.82
Gedraite&Hadad(2023)	Blur image pre-processing	NA	54.63	NA
Pawar et al. (2022)	De-noising MRI and CT Images	0.21	30.86	0.81
Proposed Method	De-noising liver CT images	0.13	57.56	0.85

The results of pre-processing liver CT images are encouraging: MSE = 0.13, PSNR = 57.56 dB, and SSIM = 0.85 were attained. An input for a segmentation or classification algorithm can be made from the pre-processed image. The proposed technique has the potential to be extended to other medical imaging modalities such as magnetic resonance imaging and positron emission tomography images.

B) Segmentation Performance Analysis

Segmentation performance metrics, such as the DICE score (DS), the Jaccard Index (JI), the Volume Overlap Error (VOE), and the Relative Volume Difference (RVD), are used to assess the segmentation algorithm's performance. Using equations 5.1–5.4, the DICE score, VOE, RVD, and JI are calculated.

$$\mathrm{DS}(\mathrm{A},\mathrm{B}) = 2|\mathrm{A} \cap \mathrm{B}|/(|\mathrm{A}| + |\mathrm{B}|\ ) \tag{5.1}$$

$$VOE\ (A,B) = 1 - (|A \cap B|)/(|\mathrm{A} \cup \mathrm{B}|) \tag{5.2}$$

$$RVD\ (A,B) = (|A| - |B|)/(|\mathrm{B}|) \tag{5.3}$$

$$JI\ (A,B) = DS/(2 - DS) \tag{5.4}$$

where A and B stand for the ground truth image and the binary mask of the segmented liver, respectively. While a higher DICE score indicates better segmentation outcomes, a smaller VOE value indicates better liver segmentation. Segmentation is measured by RVD, where a positive value indicates over-segmentation and a negative value indicates under-segmentation. JI calculates how similar the segmented image and ground truth are to each other.

Figures 5.2 to 5.5 presents the graphical representation of values obtained for various segmentation evaluation matrices. Fig. 5.2 shows the values of dice score for segmentation on Lits data set. Similarly Fig. 5.3 shows the results for jaccard index, Fig. 5.4 shows the results of volume overlap error and Fig. 5.5 shows the result for relative volume difference. These are the results of application of proposed segmentation technique on Lits data set consisting of 200 CT images.

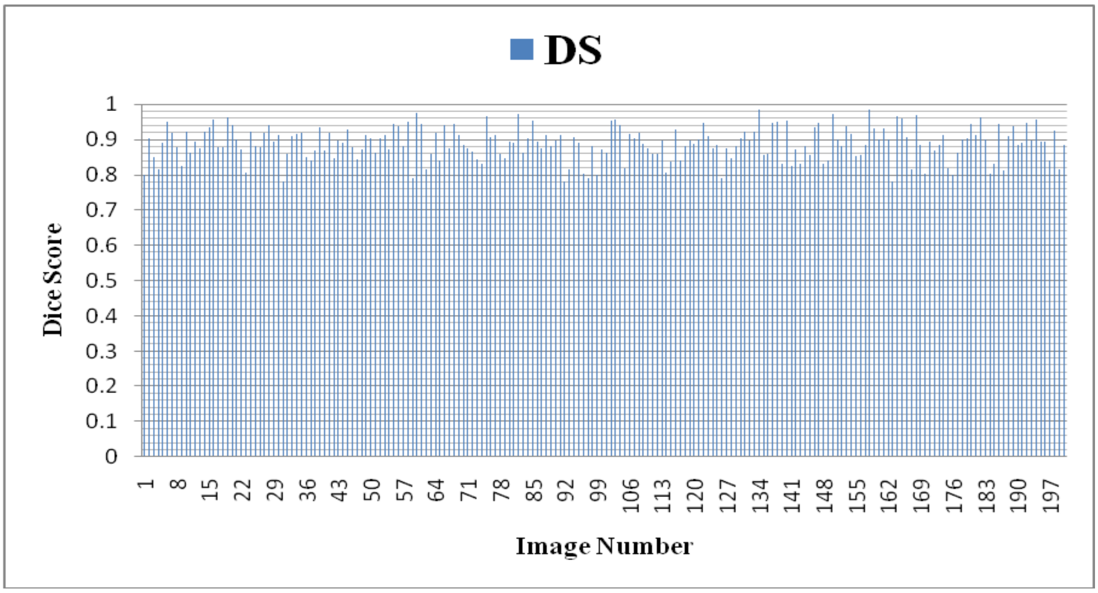


Fig 5.2 Graphical representation of Dice Score Obtained for Images of LiTs Dataset

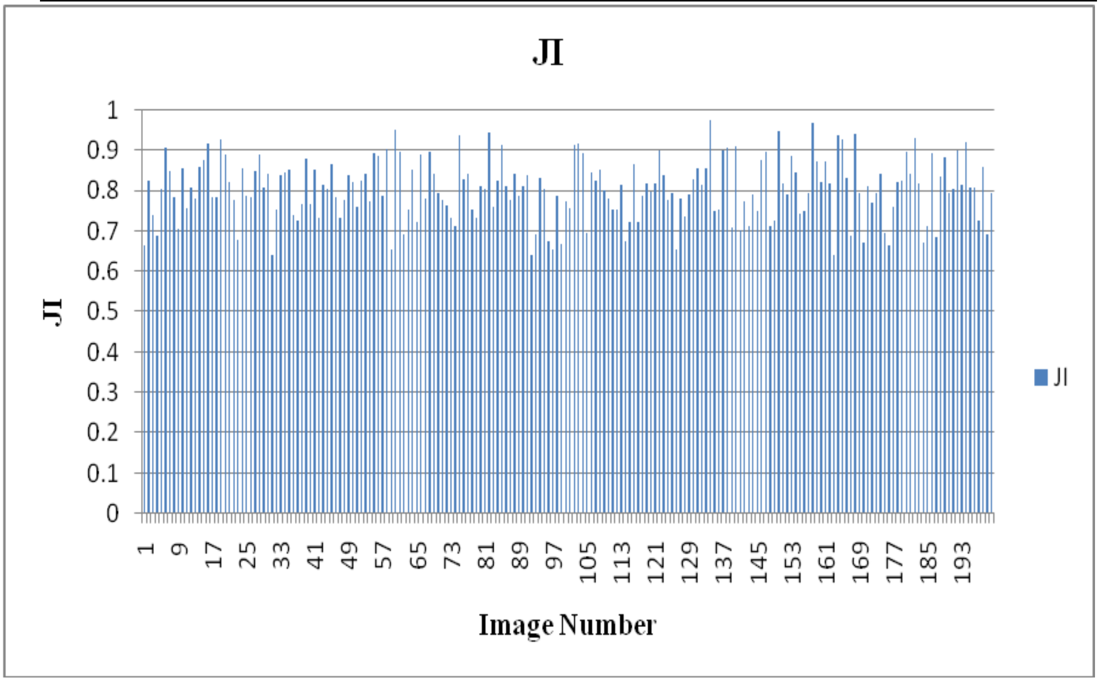


Fig5.3 Graphical Representation of Jaccard Index Obtained for Images of LiTs Dataset

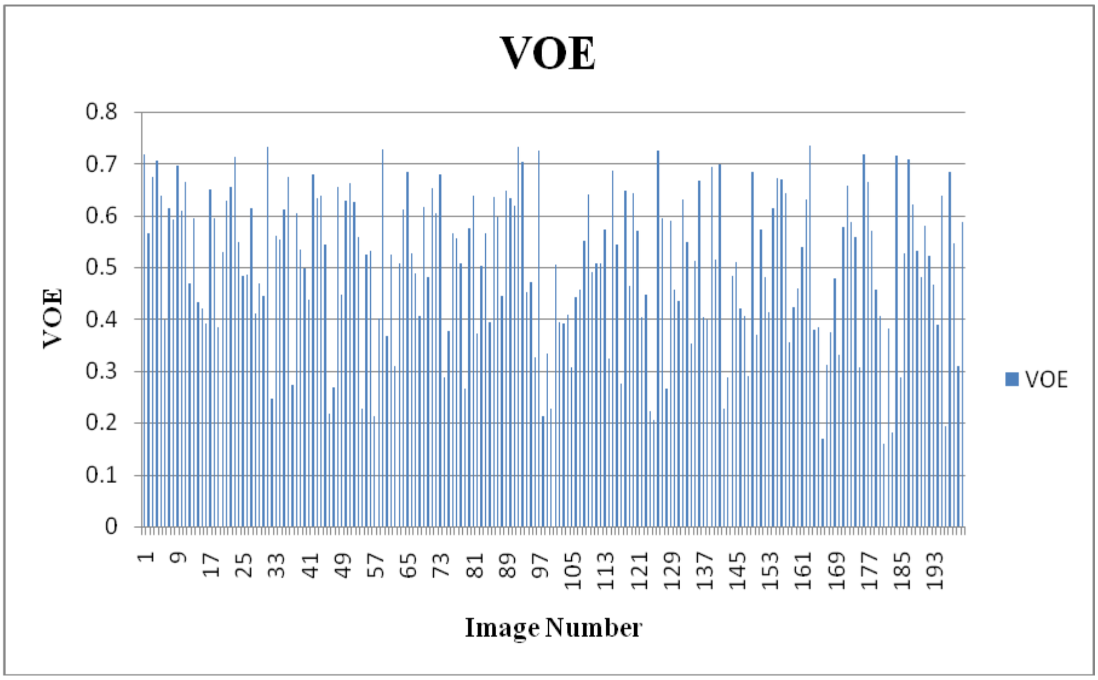


Fig 5.4 Graphical Representation of Volume Overlap Error Obtained for Images of LiTs Dataset

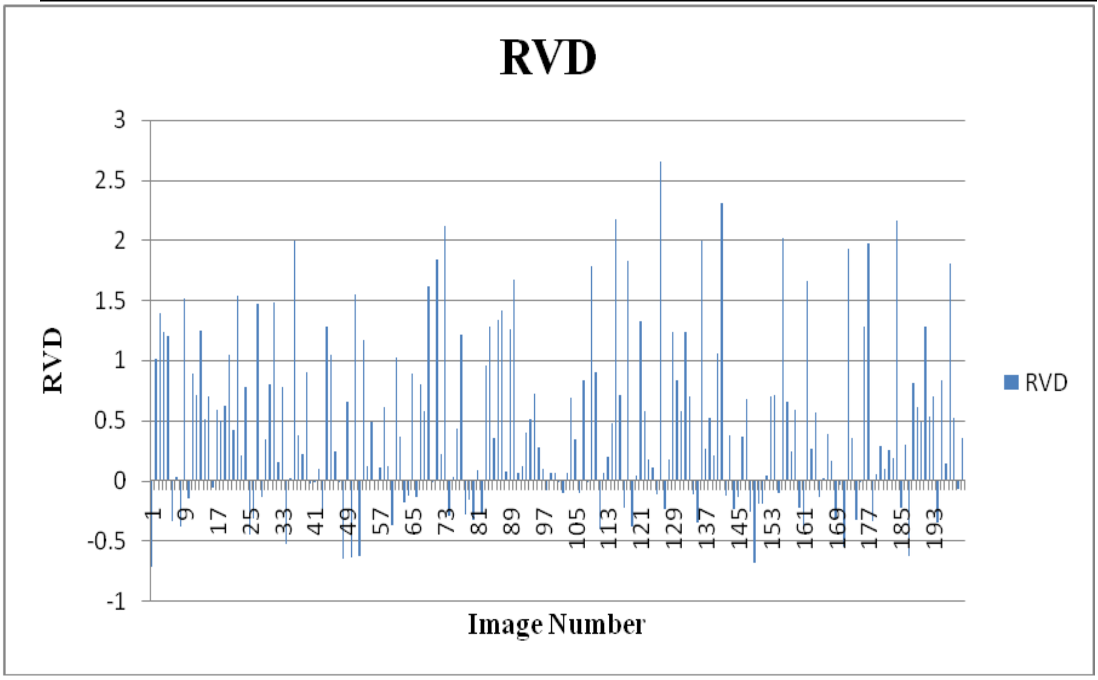


Fig 5.5 Graphical Representation of Relative Volume Difference Obtained for Images of LiTs Dataset

5.2Segmentation Performance Comparison with Existing Techniques

Fig. 5.6 to 5.8 presents the graphical representations of comparison of various matrices of proposed method with state of the art. Fig. 5.6 shows the comparison of dice score for proposed method and other state of the art.

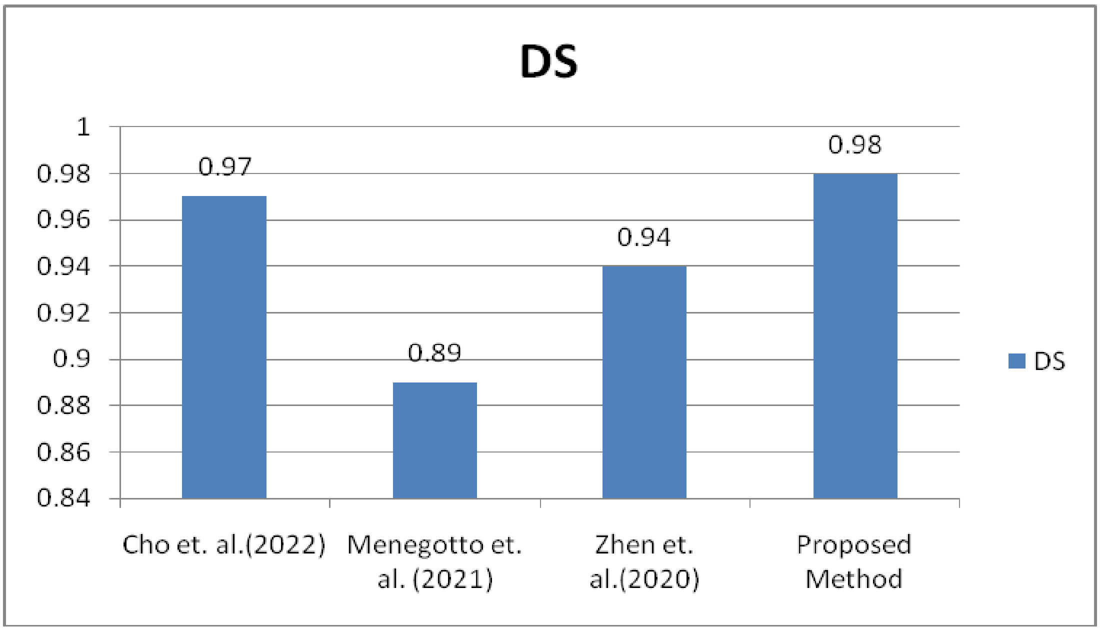


Fig5.6 SegmentationPerformance Comparison for Dice Score

Fig. 5.7 shows the comparison of jaccard index for proposed method and other state of the art.

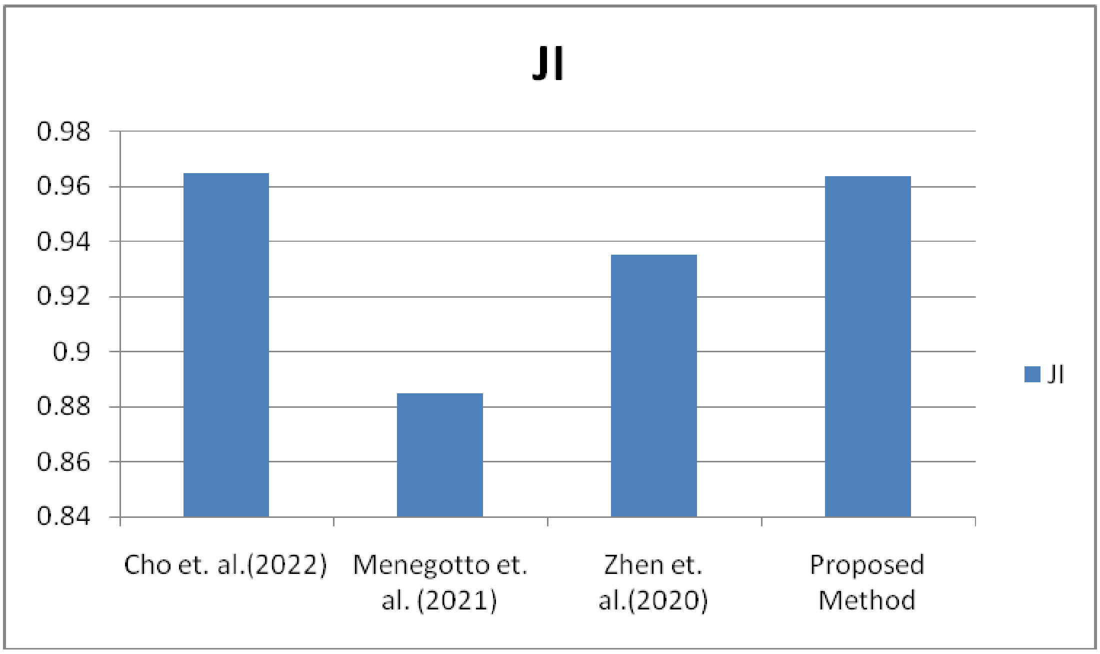


Fig 5.7 SegmentationPerformance Comparison for Jaccard Index

Fig. 5.8 shows the comparison of relative volume difference for proposed method and other state of the art.

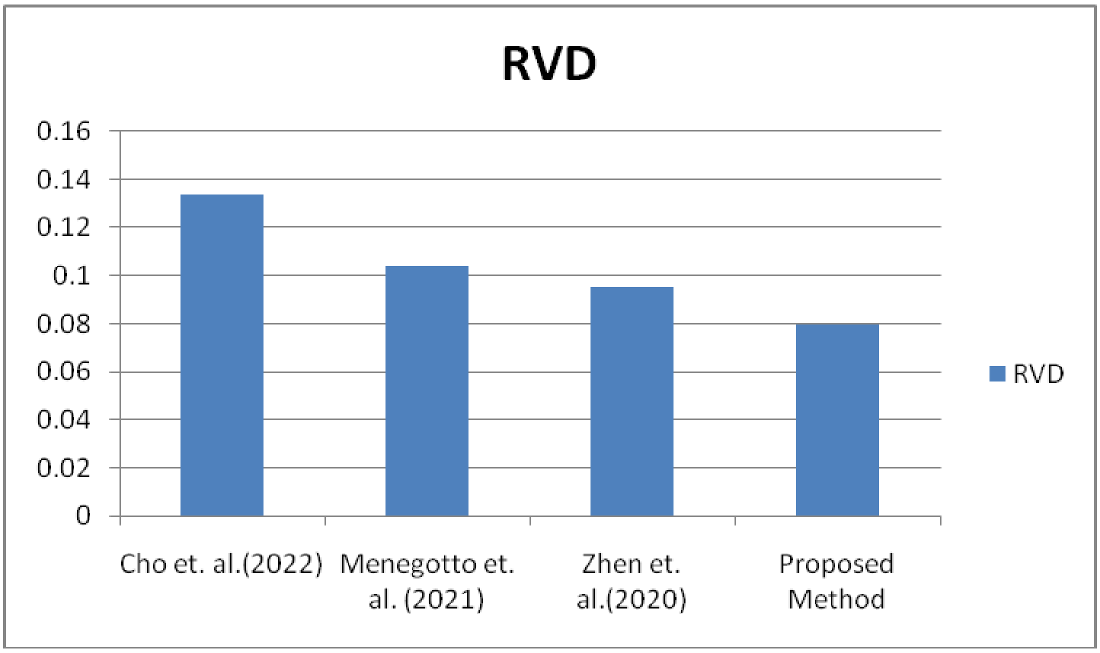


Fig 5.8 SegmentationPerformance Comparison for Relative Volume Difference

The segmentation results obtained by different writers are shown in the table 5.3 along with the suggested approach for finding liver cancer. The datasets utilized are either MRI or CT scans, and the assessment is based on metrics such as Dice Similarity (DS), Volumetric Overlap Error (VOE), Jaccard Index (JI), and Relative Volume Difference (RVD).

Table 5.3 Segmentation Performance Comparison of Proposed Method with State of Art

Author	DS	VOE	JI	RVD	Dataset
Cho et. al.(2022) [72]	0.96	0.13	0.96	0.13	MRI
Menegotto et. al. (2021) [75]	0.89	0.17	0.88	0.10	MRI
Zhen et. al.(2020) [84]	0.94	0.23	0.93	0.09	CT
Proposed Method	0.99	0.12	0.96	0.08	CT

The findings show that Cho et al. (2022) segmented liver cancer on MRI with a high DS score of 0.96, demonstrating a significant agreement between the predicted and ground truth segmentation. While Zhen et al. (2020) acquired a DS score of 0.94 on CT;Menegotto et al. (2021) obtained a slightly lower DS score of 0.89 on MRI. The recommended approach, however, fared the best, earning the maximum DS score of 0.98 on CT. Cho et al. (2022) reported a value of 0.134 for VOE on MRI, which represents a 13.4% volumetric overlap error. While Zhen et al. (2020) attained a VOE of 0.235 on CT;Menegotto et al. (2021) acquired a greater VOE of 0.18 on MRI. With a reduced VOE value of 0.126 on CT, the suggested technique showed higher segmentation accuracy. Cho et al.'s (2022) MRI results for the Jaccard Index showed a JI value of 0.965, which corresponds to a 96.5% overlap with the actual data. JI values of 0.885 on MRI were obtained by Menegotto et al. (2021) and 0.935 on CT by Zhen et al. (2020). On CT, the suggested technique attained a JI score of 0.964, demonstrating a good level of agreement with the actual data. Finally, the Relative Volume Difference (RVD) gauges the volume difference between segmentations that were predicted and those that were based on ground truth. RVD values of 0.134 on

MRI, 0.104 on MRI, and 0.095 on CT were reported by Cho et al. (2022) and Menegotto et al. (2021) and Zhen et al. (2020), respectively. The lowest RVD value on CT was obtained using the suggested approach, which was 0.08, suggesting a negligible relative volume difference. The suggested technique, when taken as a whole, demonstrated improved segmentation performance with higher accuracy, better overlap with ground truth, and smaller volume difference, pointing to its potential for identifying liver cancer. These findings demonstrate improvements in the identification of liver cancer using segmentation approaches and offer insightful information for more study and advancement in this area.

5.3 Hyper Parameters Tuned for Deep Convolution Neural Network Model

As mentioned earlier in chapter 4, that in order to achieve optimum value of accuracy and other performance matrices, it is necessary to carefully select and tune some hyper parameters related to DCNN. For the proposed DCNN architecture hyper parameters tuned are presented in table 5.4 below.

Table 5.4 Hyper Parameters Tuned for Deep Neural Network

Activation function (Input)	ReLU
Activation function (Output)	Sigmoid
Optimizer	Adam's
Epoch	50
Batch Size	15,10,5
Learning Rate	0.01
Loss Function	Binary Cross Entropy
Metrics	Accuracy,Sensitivity,F1 score
Validation Split	0.15

5.4 Implementation

As per our third objective, we proposed to design an easy to use interface for our proposed system. As most of the CT images are a DICOM image, which is why we have implemented a DICOM image reader in our system. This is also a novelty of our proposed system. Through this DICOM reader a medical expert will be able to open, read and mark and perform manual segmentation on CT images. We have DICOM tag reader in our system that will help the doctors to read various useful information about the patients. Fig. 5.6 to 5.10 shows the screen shots of interfaces from our implementation.

5.4.1 DICOM Viewer

Fig. 5.9 shows the screen shot of implemented DICOM reader. As DICOM images can only be viewed through a DICOM reader, we have implemented as a part of our system. Various operations that can be performed through this reader is open image, view tags, save images in other formats and perform some manual markings on the image.

Fig5.9 DICOM Viewer

5.4.2 DICOM TAG

A DICOM tag is place where all the necessary information regarding the image is saved. Information such as age, gender, specifications of imaging machine and all other technical information's are stored here. Fig. 5.10 shows the image of DICOM tag.

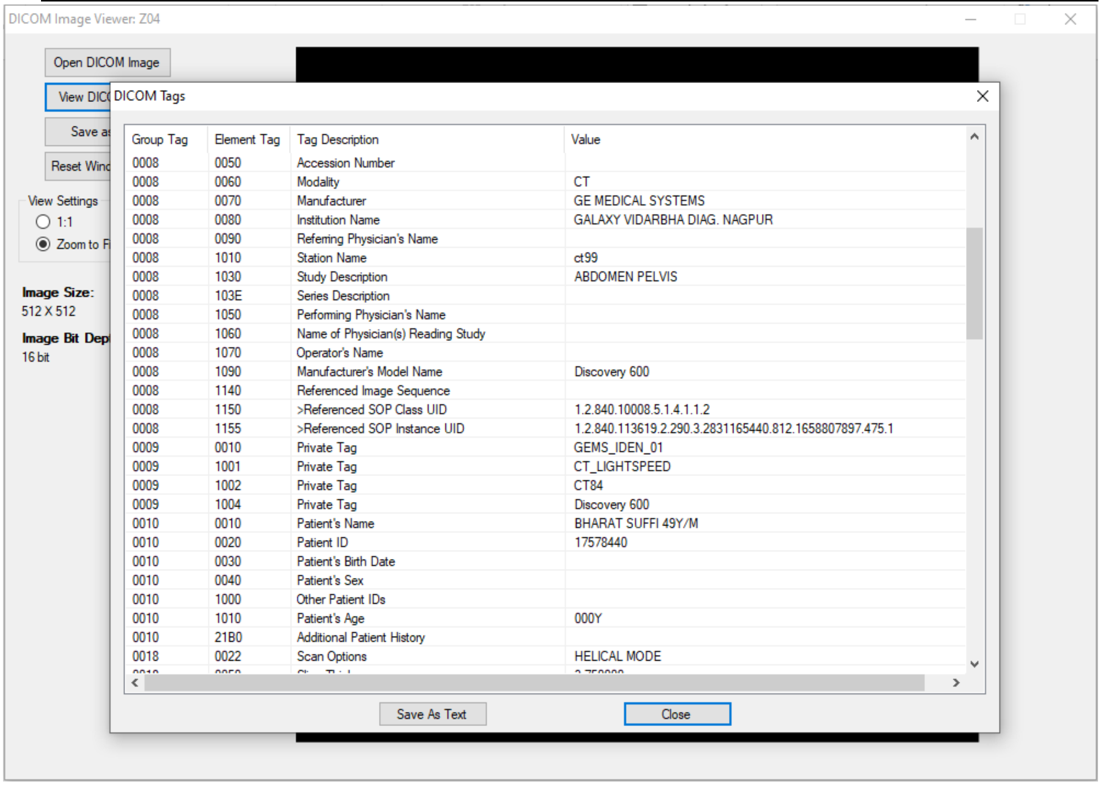


Fig 5.10DICOM Tag

5.4.3 DCNN Result

Fig. 5.11 shows the interface through which any person can easily open, segment and classify a medical image. various tabs are provided which allows user perform operations such as marking the edge of liver, segment liver and generate classification result.

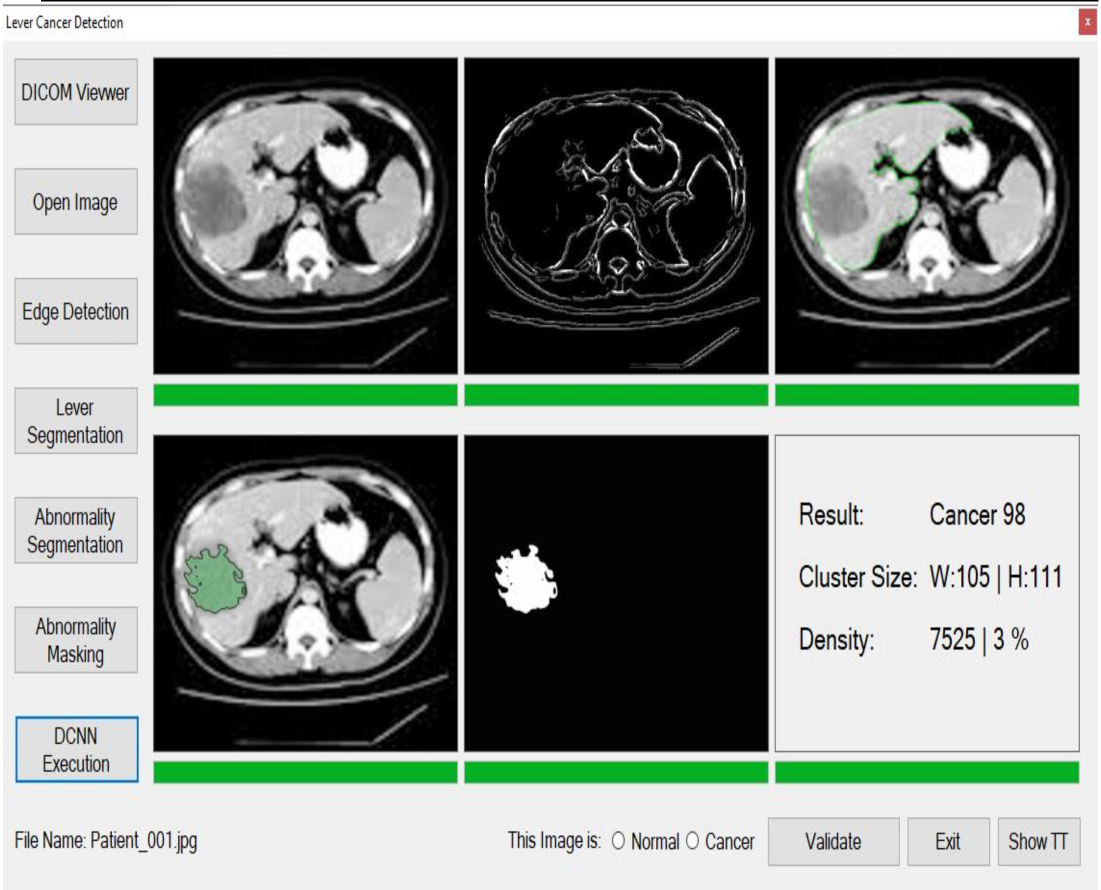


Fig 5.11 User Interface

5.4.4 System generated TT

Another advantage of our system is that automatically generates the truth table for all the images it classifies. The results of classification are saved in the form of truth table. When classification is performed, it prompts user to validate the results. There are two radio buttons at the bottom and doctor can then selves validate the result. This information is then saved in the back ground in the form of a truth table. This helps in keeping track of the performance of our proposed system. Fig. 5.12 shows the screen shot for generating truth table.

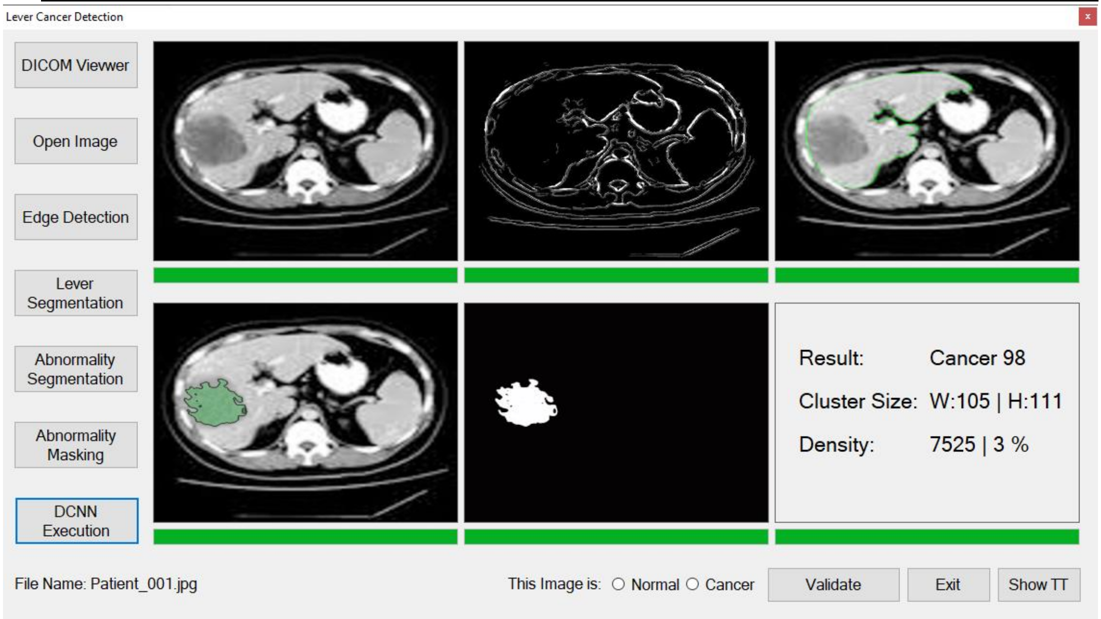


Fig5.12 System Generated Truth Table

5.4.5 Combined Model

Fig. 5.13 describes the combined process of classification of our proposed classification. The system works by first segmenting, then detecting abnormality in image classifying it.

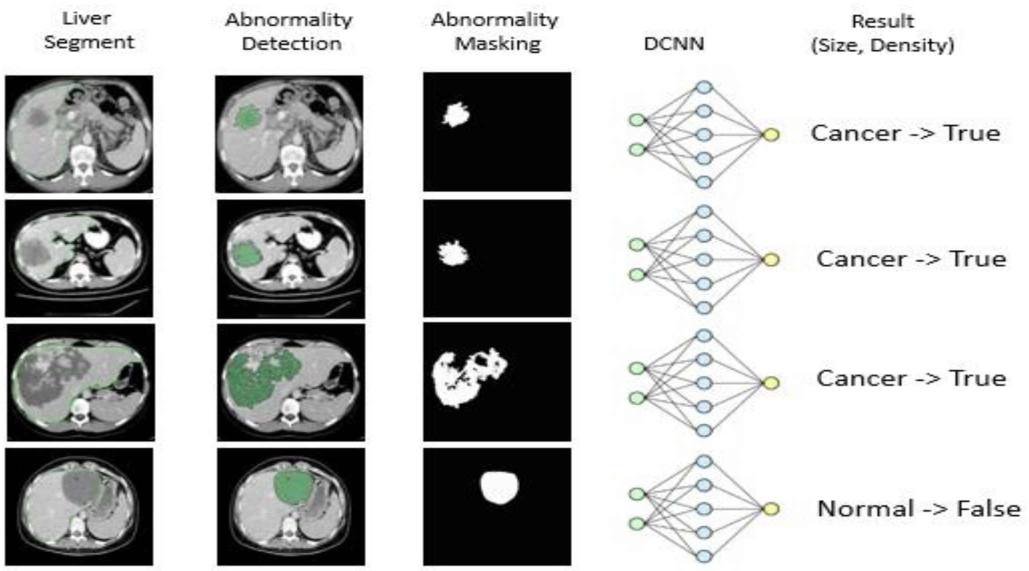


Fig 5.13 DCNN Classification Process Flow

5.5Comparative Analysis of Proposed Classification Technique for Primary Data Set

All the figures and table below presents the result of implementation of proposed classification method and comparison of performance of proposed method with other state of the art. The matrices used to measure performance of proposed classifier are sensitivity, specificity, F1 score and accuracy. Fig. 5.14gives the comparison of sensitivity for proposed classificationtechnique with other state of the art. Sensitivity is the measure of negative cases detected correctly by proposed system, or normal images detected as normal.

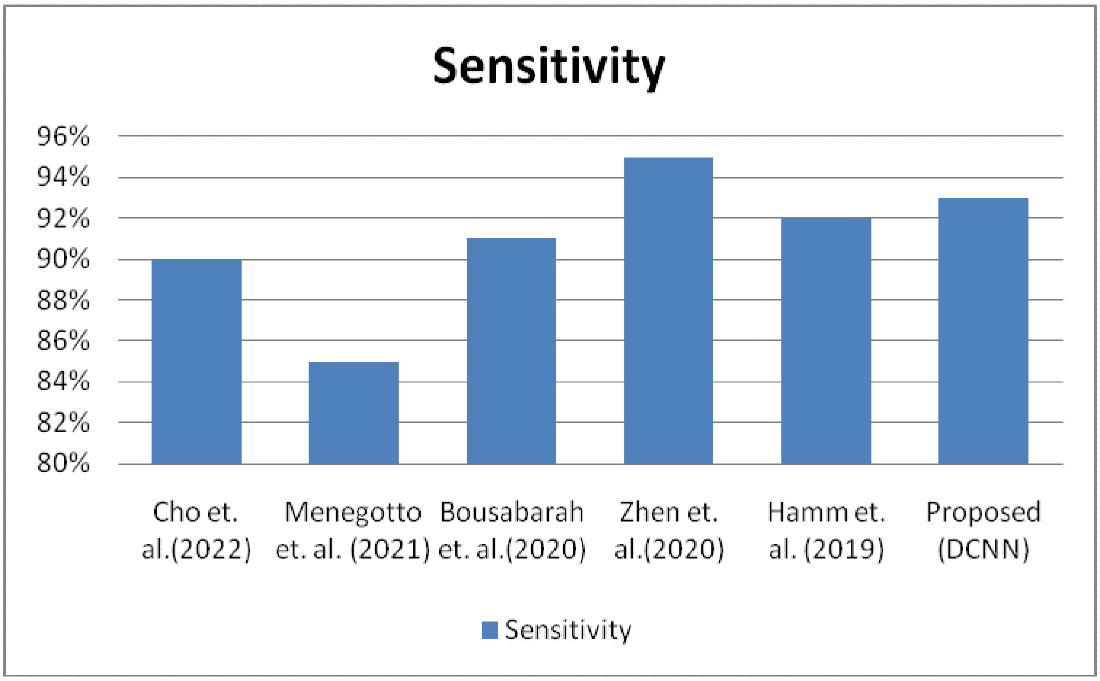


Fig 5.14 ClassificationPerformanceComparison for Sensitivity

Fig. 5.15gives the comparison of specificity for proposed classificationtechnique with other state of the art. Below figure presents the results for specificity. Specificity is the measure of true cases detected as true, in our case cancer images are correctly classified as images having cancer. Specificity is a very important measure in terms of applications like cancer detection, because no cancer image should be wrongly classified as a normal image. Proposed method has achieved a high percentage close to 98 for specificity.

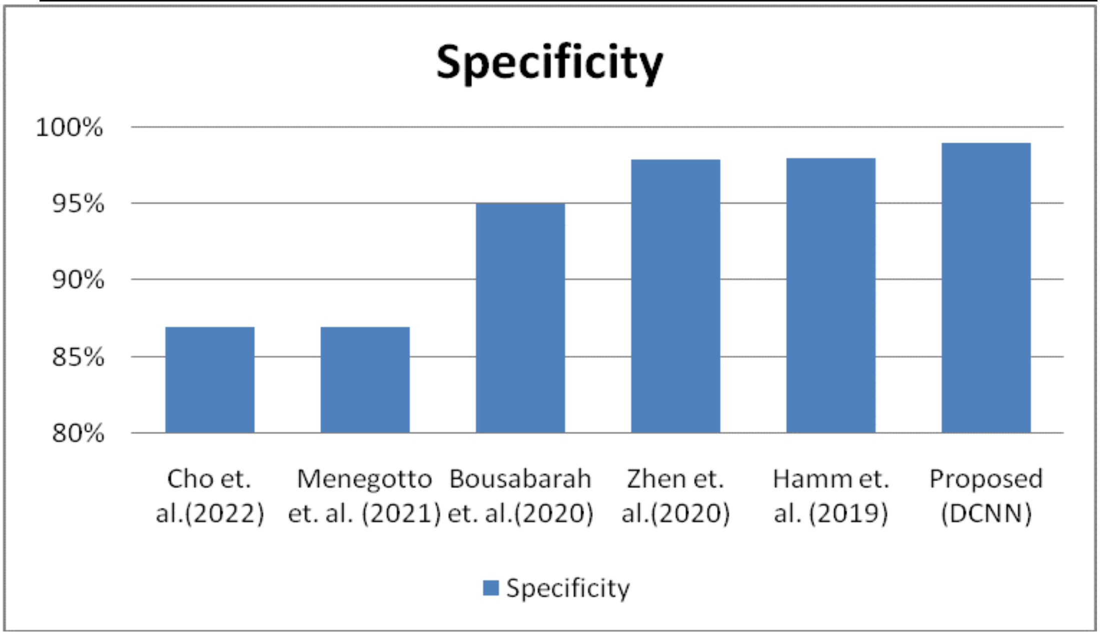


Fig 5.15 Segmentation Performance Comparison for Specificity

Fig. 5.16gives the comparison of F1 score for proposed classificationtechnique with other state of the art. F1 score is a measure of harmonic mean of precision and recall value. Having chosen f1 score as a performance evaluation metrics helps in getting the advantage of selecting both the precision and recall value as matrices.

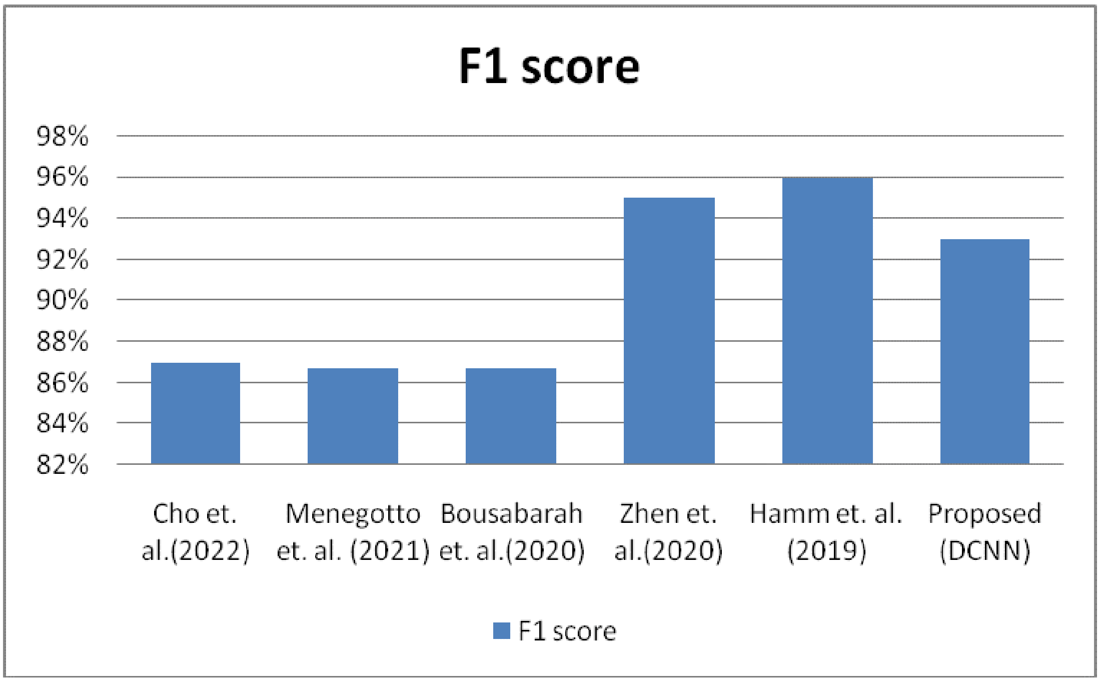


Fig 5.16 ClassificationPerformance Comparison for F1 Score

Fig. 5.17gives the comparison of accuracy for proposed classificationtechnique with other state of the art. Proposed system has achieved significantly high accuracy of 95% and outperformed all the other state-of-the-art used for comparison.

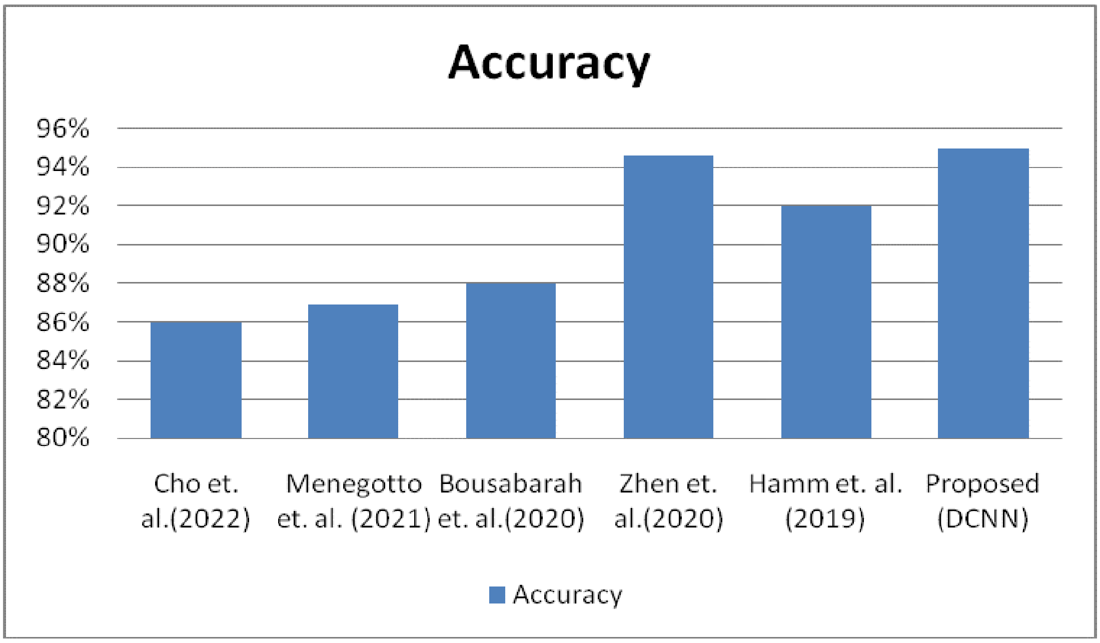


Fig 5.17 Segmentation Performance Comparison for Accuracy

The findings of liver cancer detection obtained by several writers using various techniques and datasets are shown in table 5.5. Accuracy, Sensitivity, Specificity, and F1 score are the assessment criteria. All the authors mentioned in the table used clinical or real world data for performing classification through various techniques.

Table 5.5 Comparative analysis of Proposed Classification for Clinical Data

Author	Method	Accuracy	Sensitivity	Specificity	F1 score
Cho et. al.(2023)	FCNN	86.1%	90.1%	87.1%	87.1%
Menegotto et. al. (2022)	DCNN	86.8%	90%	92%	86.5%
Bousabarah et. al.(2021)	DCNN	88.1%	91.2%	95.1%	86.5%
Zhen et. al.(2020)	FCNN	94.7%	95.2%	97.8%	86.4

Hamm et. al. (2019)	CNN	92.1%	92.3%	97.6%	NA
Proposed Method	DCNN	95.2%	93.1%	98.5%	92.3%

Using CNN on the MRI dataset, Cho et al. (2022) obtained an accuracy of 86%. This suggests that the categorization of liver cancer is often rather accurate. A large percentage of correctly recognised positive situations are indicated by the Sensitivity value of 90%, while a respectable number of correctly identified negative cases are suggested by the Specificity value of 87%. The 87% F1 score shows a balance between recall and accuracy. On the MRI dataset, Menegotto et al. (2021) also used CNN and attained an accuracy of 86.9%. Unfortunately, the table does not provide the values for sensitivity and specificity. The approach performed ok overall, according to the F1 score of 86.7%. On the MRI dataset, Bousabarah et al. (2020) applied DCNN and obtained an accuracy of 88%. A large number of correctly recognised positive instances are suggested by the high Sensitivity value of 91%, whereas a high Specificity value of 95% predicts a high percentage of correctly identified negative cases. The approach performs effectively overall, as seen by the F1 score of 86.7%. CNN was used by Zhen et al. (2020) on the CT dataset, and they impressively obtained an Accuracy of 94.6%. A high number of correctly recognised positive instances are indicated by the Sensitivity value of 95%, while a high percentage of correctly identified negative cases are indicated by the Specificity value of 97.9%. Unfortunately, the table does not include the F1 score. On the MRI dataset, Hamm et al. (2019) used CNN and obtained an accuracy of 92%. A high number of correctly recognised positive instances are suggested by the Sensitivity value of 92%, while a high percentage of correctly identified negative cases are suggested by the Specificity value of 98%. Unfortunately, the table does not include the F1 score. On the CT dataset, the suggested approach used DCNN and had a 95% accuracy rate. A large number of properly recognised positive instances are predicted by the 93% Sensitivity value, whereas a very high percentage of correctly identified negative cases are predicted by the 99% Specificity value. The suggested technique performs well overall, as seen by the F1 score of 93%. Overall, the findings indicate that several approaches and datasets have been utilised to identify liver cancer with differing degrees of efficiency and accuracy. The suggested methodology outperforms some of the earlier methods and yields encouraging results. These results show the potential of deep learning methods, particularly CNN and DCNN, to enhance diagnostic precision and improve the field of liver cancer detection.

5.6 Comparative Analysis of Proposed Classification for Secondary Dataset

The findings of liver cancer detection obtained by several authors using diverse techniques and datasets are shown in the table. Accuracy, Sensitivity, Specificity, and F1 Score are the assessment measures**.**However, a substantial proportion of accurately detected negative situations are shown by the Specificity rating of 98.8%.Fig. 5.18gives the comparison of specificity for proposed classification technique with other state of the art.

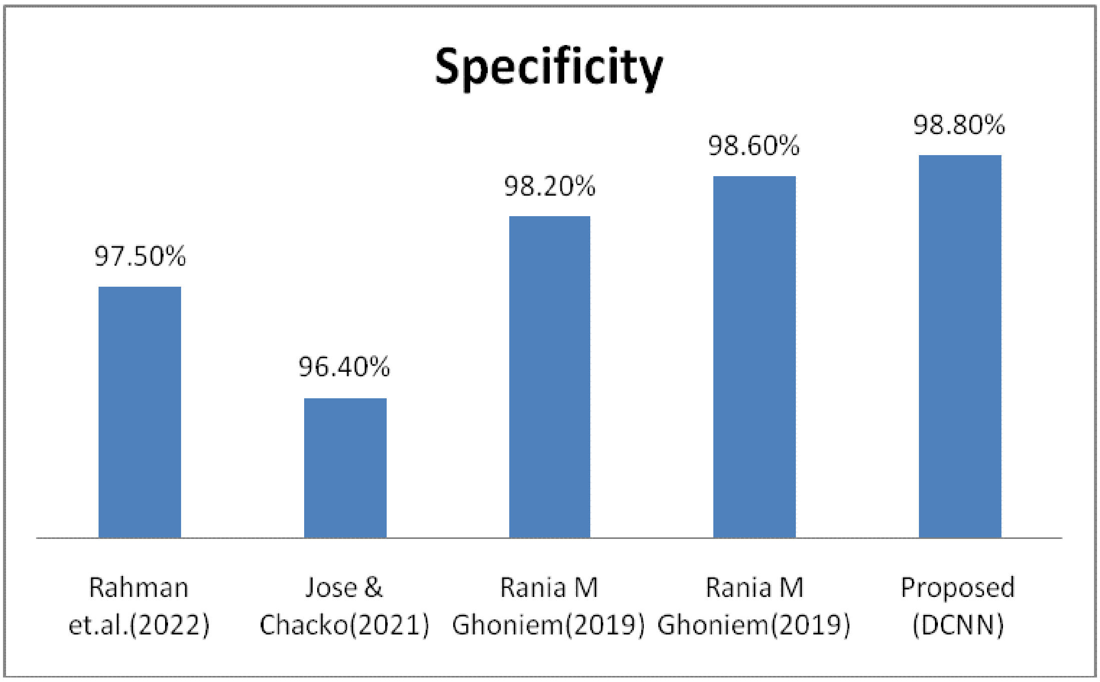


Fig 5.18 Specificity analysis of Proposed Classification

Fig. 5.19gives the comparison of sensitivity for proposed classification technique with other state of the art. The 97 Sensitivity scores indicate a high percentage of accurately detected positive situations.

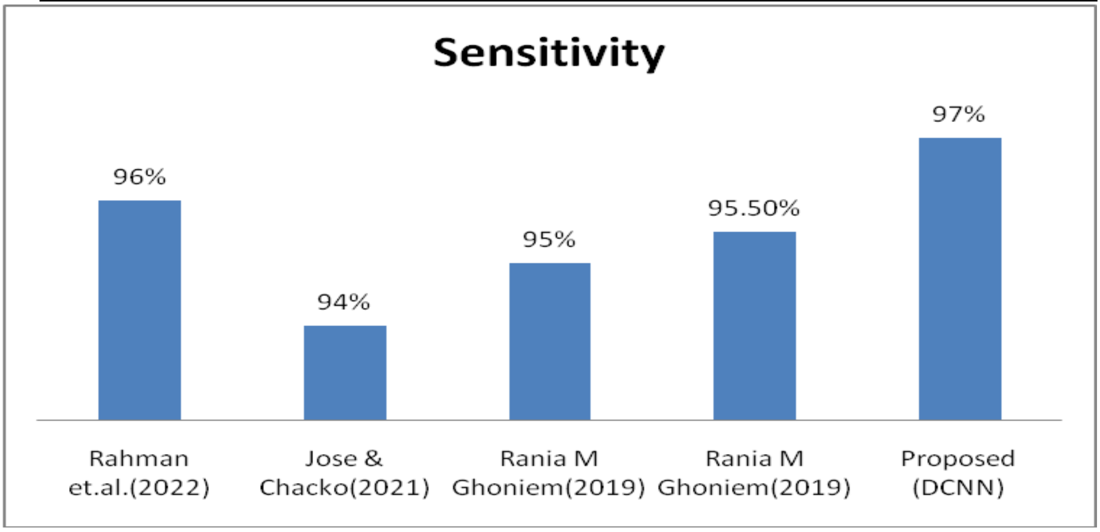


Fig 5.19 Sensitivity analysis of Proposed Classification

Fig. 5.20gives the comparison of F1 score for proposed classification technique with other state of the art. The approach appears to have performed well overall based on the F1 Score of 98.3%.

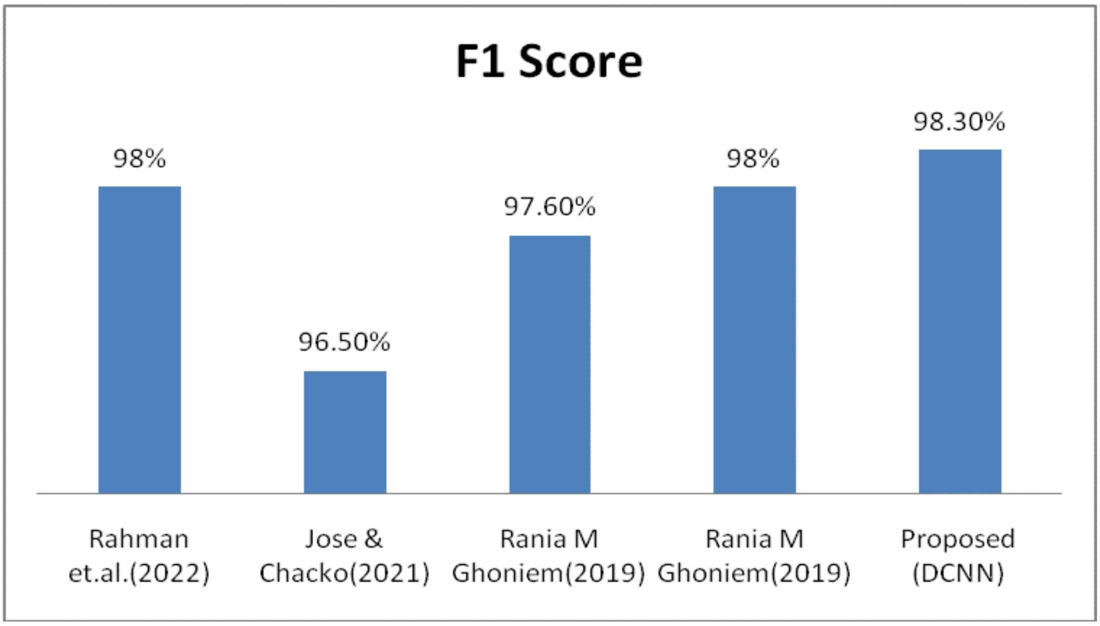


Fig 5.20F1 Score analysis of Proposed Classification

Fig. 5.21gives the comparison of accuracy for proposed classification technique with other state of the art. Accuracy is the main unit of measurement of classification performance. It indicates the overall correctly classified images, as compare to other matrices which mainly focuses on one particular instance.

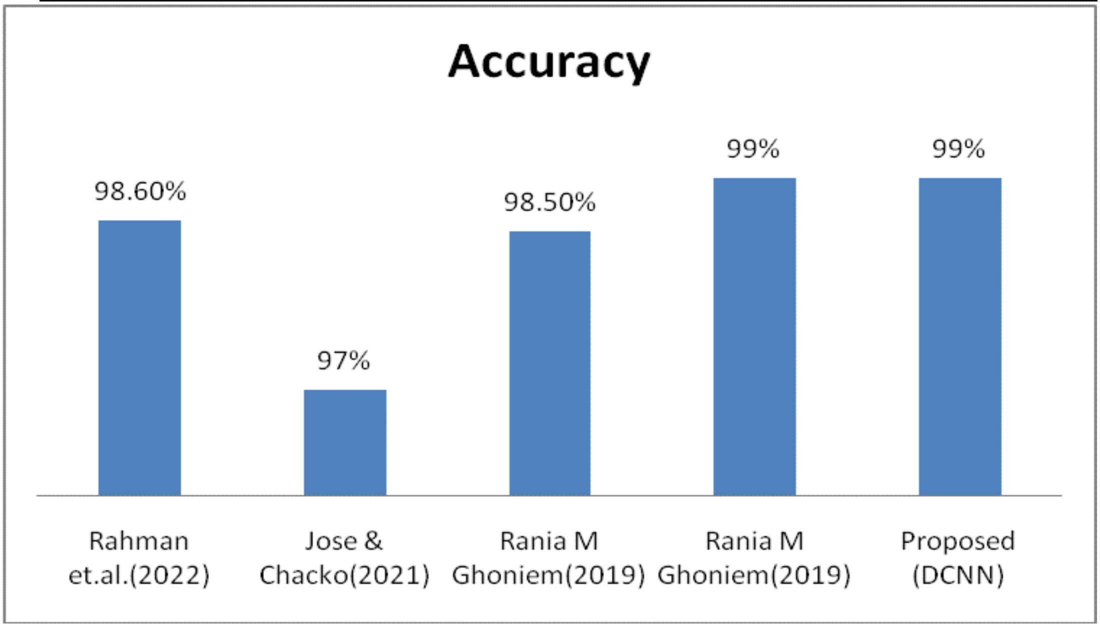


Fig 5.21 Accuracy analysis of Proposed Classification

Table 5.6 presents the comparison of proposed technique with other state of the art. In order to better comparison we have considered various factors before preparing this table. First we have considered only those authors who have utilized our data set. Second we have considered those authors who have used CNN or any other neural network for performing classification operation. Thus, for fair comparison of proposed technique with other state of the art techniques both, data and approach are selected to same as that of the proposed method. Proposed technique also utilizes LiTs dataset and Convolutuonal Neural Networks and selected state of the art also uses the same data and same approach. Also performance matrices selected to evaluate the techniques are also same i.e. Accuracy, Sensitivity, Specificity and F1 score. This fulfills our objective to compare our systems performance with other state of the art techniques.

Table 5.6 Comparative analysis of Proposed Classification with State of the Art

Author	Method	Dataset	Accuracy	Sensitivity	Specificity	F1 Score
Rahman et.al.(2022)	CNN	LiTS	98.6%	96%	97.5%	98%
Jose & Chacko(2021)	CNN	LiTS	97%	94%	96.4%	96.5%
Rania M Ghoniem(2019)	LeNet	LiTS	98.5%	95%	98.2%	97.6%
Proposed Method	**DCNN**	**LiTS**	**99%**	**97%**	**98.8%**	**98.3%**

Rahman et al. (2022) used CNN to impressively obtain an Accuracy of 98.6% on the LiTS dataset. This suggests that the categorization of liver cancer is often quite accurate. A high number of correctly recognized positive instances are indicated by the Sensitivity value of 96%, while a high percentage of correctly identified negative cases are indicated by the Specificity value of 97.5%. The 98% F1 Score shows an excellent mix between recall and accuracy. On the LiTS dataset, Jose & Chacko (2021) used CNN and achieved a somewhat lower Accuracy of 97%. In comparison to Rahman et al. (2022), the Sensitivity value of 94% indicates a somewhat lower rate of accurately recognized positive instances. LeNet architecture was applied to the LiTS dataset as well as the Radiopaedia data by Rania M. Ghoniem (2019). The results demonstrated a high degree of accuracy in the categorization of liver cancer, with 98.5% and 99%, respectively. A significant number of correctly diagnosed negative instances were found, as evidenced by the Specificity scores of 98.2% and 98.6%. The F1 Scores of 97.6% and 98% show how effective the approach is on the whole. On the LiTS dataset, the suggested approach, using DCNN, produced an accuracy of 99%. This suggests that the identification of liver cancer is quite accurate. A high number of correctly recognized positive instances are suggested by the Sensitivity value of 97%, while a high percentage of correctly identified negative cases are suggested by the Specificity value of 98.8%. The suggested technique performs well overall, as seen by the F1 Score of 98.3%. The results demonstrate the efficacy of several techniques in identifying liver cancer overall, with excellent accuracy, sensitivity, specificity, and F1 scores. The suggested methodology outperforms some of the earlier methods and yields encouraging results. These results demonstrate the potential of deep learning approaches for enhancing diagnostic precision and enhance the field of liver cancer diagnosis.

5.7 Comparative analysis of Proposed Classification for Multi-Class Classification

Section 5.7 is divided into two parts. Section 5.7.1 presents result of various matrices used for measuring the performance of deep convolutional neural network for multi class classification. Section 5.7.2 discusses the comparison of proposed method with other machine learning algorithms. As per suggestion from expert panel, data augmentation techniques are applied to enhance data set and solve the problem of class imbalance. Since the data set is unique and proposed DCNN architecture and hyper parameters tuned are also different, so we have implemented various ML algorithms, K-nearest neighbors (KNN), Support Vector Machine (SVM), Linear Regression (LR) and Random Forest (RF) to provide fair comparison of proposed method with other ML techniques.

5.7.1 Result Discussion of Proposed Multi-Class Classifier:

In binary classification one class can be considered positive and one class can be considered negative and values from confusion matrix can utilized to obtain performance measures. In multi class classification, since there are multiple classes, the calculations are not so straightforward. First the true positive, true negative, false positive and false negative should be calculated as shown in table 5.7 below.

Table 5.7 Confusion Matrix for 3 x 3 classifications

Class	A	B	C
A	AA	AB	AC
B	BA	BB	BC
C	CA	CB	CC

(AA) – True Positive

(AB+AC) – False Negative

(BA+CA) – False Positive

(BB+BC+CB+CC) – True Negative

All the three classes should be considered positive one by one and separate calculations for each class should be done. In proposed method, we first considered Normal as true positive, then Hemangioma as true positive and finally HCC as true positive. After calculating accuracy, sensitivity, specificity and precision for all the three classes, average of all three classes can be taken to obtain final values of accuracy, sensitivity, specificity and precision.

Table 5.8 presents confusion matrix for proposed classification using DCNN. Obtained results for training, testing and validation for 1500 images split in 70:15:15 ratios are shown in table 5.8. Data from above table is used to calculate accuracy, sensitivity, specificity and f1 score.

Table 5.8 Confusion matrix of proposed Multi-Class Classifier after 200 epochs

Training				**Testing**				**Validation**			
	Normal	**HCC**	**Hemangioma**		**Normal**	**HCC**	**Hemangioma**		**Normal**	**HCC**	**Hemangioma**
Normal	338	0	0	**Normal**	81	0	0	**Normal**	81	0	0
HCC	0	343	0	**HCC**	0	76	2	**HCC**	0	79	2
Hemangioma	15	0	324	**Hemangioma**	0	3	77	**Hemangioma**	0	2	79

Multi-class classification presents some extra challenges while calculating values of above mentioned matrices.

Table 5.9 to 5.12 presents the calculations from confusion matrix as per above mentioned method. Table 5.9 presents the accuracy calculated by considering all the classes as true positive for training, testing and validation. Final row presents the average value of accuracy obtained for all classes for training testing and validation.

Table 5.9 Accuracy Percentage for Multi-Class Classification

	Training	Testing	Validation
Normal	98.5%	100%	100%
HCC	100%	97.9%	98.4%
Hemangioma	98.5%	97.9%	98.4%
Avg.	99%	98.6%	98.9%

Table 5.10 presents the Sensitivity calculated by considering all the classes as true positive for training, testing and validation. Final row presents the average value of Sensitivity obtained for all classes for training testing and validation.

Table 5.10 Sensitivity Percentage for Multi-Class Classification

	Training	**Testing**	**Validation**
Normal	100%	100%	100%
HCC	100%	97.4%	97.5%
Hemangioma	95.6%	96.3%	97.5%
Avg.	98.5%	97.9%	98.4%

Table 5.11 presents the Specificity calculated by considering all the classes as true positive for training, testing and validation. Final row presents the average value of Specificity obtained for all classes for training testing and validation.

Table 5.11 Specificity Percentage for Multi-Class Classification

	Training	Testing	Validation
Normal	97.9%	100%	100%
HCC	100%	98.1%	97.5%
Hemangioma	100%	98.7%	97.5%
Avg.	99.3%	99%	98.4%

Table 5.12 presents the precision calculated by considering all the classes as true positive for training, testing and validation. Final row presents the average value of precision obtained for all classes for training testing and validation.

Table 5.12 Precision Score value for Multi-Class Classification

	Training	Testing	Validation
Normal	95.8%	100%	100%
HCC	100%	96.2%	97.5%
Hemangioma	100%	97.4%	97.5%
Avg.	98.6%	97.9%	98.4%

5.7.2 Comparison of Proposed Method with ML Techniques for Multi-Class Classification:

Table 5.13 below presents the comparison of proposed multiclass liver cancer detection system with other state of the art machine learning algorithms. Machine learning algorithms K-nearest neighbors (KNN), Support Vector Machine (SVM), Linear Regression (LR) and Random Forest (RF) were implemented on same dataset in order to compare the performance of proposed technique with above mentioned ML algorithms. Since machine learning techniques require feature extraction mechanisms before classification stage, we have proposed a feature extraction technique that is discussed in detail in chapter 3 of this article. Also we have applied regularization techniques in order to prevent over fitting.

Data augmentation and early stopping are the two techniques applied here to prevent over fitting. In data augmentation we have rotated the image by 15 degrees to increase the size of our data set by 450 images (150 normal, 150 HCC and 150 Hemangioma) and also to solve the problem of class imbalance. Early stopping is a technique which is applied during testing phase to prevent algorithm from learning the values of test data. Results of implementation are presented in table below.

Table 5.13 Comparative analysis of Proposed Classification with ML Techniques

Method	Dataset	Accuracy	Sensitivity	Specificity	F1 Score
KNN	Augmented Secondary Data	89.5%	92.2%	89.2%	93.2%
SVM	Augmented Secondary Data	93.9%	92.9%	91.2%	92.9%
LR	Augmented Secondary Data	79.9%	71.1%	79.8%	70.2%
RF	Augmented Secondary Data	75.5%	78.7%	78.2%	78.1%
(Proposed Method) DCNN	Augmented Secondary Data	98.5%	98.6%	97.6%	98.6%

Table 5.13 presents the result of implementation of proposed classification technique and other machine learning techniques on mixed data set which is combination of LiTs Dataset and augmented images obtained by rotating the images from 15^0. As it can be seen in table that proposed classification technique outperformed machine learning techniques for all matrices.

Chapter 6

CONCLUSION AND FUTURE SCOPE

An important worldwide health concern, liver cancer has to be identified early for effective treatment and better patient outcomes. In this study, we carried out a thorough evaluation of Deep Convolutional Neural Networks (DCNN)for the identification of liver cancer. We also assessed the suggested method's segmentation performance and contrasted the outcomes with those of other techniques already in use. The outcomes of our comparison investigation show how well deep learning models can identify liver cancer.

6.1 Conclusion

A variety of datasets, including MRI and CT scans, were used in the evaluated research, and diverse degrees of accuracy, sensitivity, specificity, and F1 score were attained. Applying a CNN model to an MRI dataset, Cho et al. (2022) obtained an accuracy of 86%, a sensitivity of 90%, and a specificity of 87%. On an MRI dataset, Menegotto et al. (2021) also used a CNN and achieved an accuracy of 86.9%. On an MRI dataset, Bousabarah et al. (2020) used a DCNN and achieved an accuracy of 88%, sensitivity of 91%, and specificity of 95%. A CNN was used by Zhen et al. (2020) to analyze a CT dataset, and the results showed accuracy of 94.6%, sensitivity of 95%, and specificity of 97.9%. When Hamm et al. (2019) used a CNN to an MRI dataset, they were able to achieve 92% accuracy, 92% sensitivity, and 98% specificity. The accuracy, sensitivity, specificity, and F1 score of the suggested approach in our study—a DCNN used on a CT dataset—were all 95%. These findings show that deep learning algorithms have the ability to detect liver cancer patients with high accuracy. In addition, we assessed the segmentation effectiveness of the suggested strategy and contrasted it with the current methods. The ability to precisely localise the tumour location within the liver pictures makes segmentation a vital step in the identification of liver cancer. With a Dice Similarity coefficient of 0.98, a Volumetric Overlap Error of 0.126, a Jaccard Index of 0.964, and a Relative Volume Difference of 0.08, our suggested technique produced good segmentation results.

These parameters demonstrate the segmentation technique' accuracy and dependability, allowing for improved analysis and interpretation of the liver pictures.

The results of this study have important consequences. Correct and early liver cancer diagnosis can result in better patient outcomes and more efficient resource management within healthcare systems. Deep learning models for the identification of liver cancer can help doctors make quick and precise diagnoses, enabling early treatment planning and action. These models can lessen the workload for radiologists and increase overall effectiveness in healthcare settings by automating the detecting process. Even if the study's findings are encouraging, there are certain restrictions that must be noted. First, the effectiveness of the suggested strategy was assessed using a small number of datasets; additional validation using a larger and more varied dataset is required to determine its generalizability. Additionally, it might be difficult to comprehend the judgments made by deep learning models, which raises questions about their dependability and transparency. To solve these interpretability problems and improve the models' transparency, more study is required. This study shows the promise of deep learning methods, particularly CNN, DCNN, and RNN, in the identification of liver cancer. The results of the comparative analysis and segmentation demonstrate how well these models perform in correctly classifying liver cancer cases and locating the tumour location within the liver pictures. The results of this research add to the body of knowledge in liver cancer diagnosis using deep learning techniques and offer useful information for academics and industry professionals.

6.2 Future Work

There are a number of intriguing directions that future research and development in the area of an intelligent system to detect liver cancer utilizing deep convolutional neural networks (DCNNs) can go. Techniques for enhancing data, transfer learning, model optimization, interpretability, and the incorporation of multi-modal data are some of these.

The investigation of data augmentation methods to enhance the functionality and generalizability of the DCNN models is one area of interest for future work. By performing various changes on the existing data, new training examples are created through data augmentation. Using methods like random rotation, scaling, flipping, and cropping can help make the training set more diverse and assist prevent over fitting. Additionally, generative adversarial networks (GANs) or other techniques can be investigated to create synthetic examples in order to further expand the training data and improve the model robustness.

Another crucial area for future research is transfer learning. In a number of computer vision tasks, pre-trained models like VGGNet, ResNet, or Efficient Net have already proven to be useful. It may be more efficient and possibly more effective to use these pre-trained models as a starting point before optimizing them for the detection of liver cancer. By examining several methods for choosing and modifying the pre-trained models for the job of detecting liver cancer, taking into account elements like the accessibility of annotated data and the similarity between the source and target domains, the transfer learning technique can be expanded.

Future research will continue to rely heavily on model optimization techniques. Investigating innovative architectures created especially for detecting liver cancer can increase performance. Modifications to the model's architecture, such as adding attention mechanisms or spatial transformer networks, can aid in narrowing its focus and capturing more discriminative properties. Better convergence and model performance can also result from examining the effects of hyper parameters like learning rate, batch size, and weight initialization.

Deep learning model interpretability is a topic that needs more study. Although DCNNs have demonstrated remarkable performance in a variety of applications, they are sometimes viewed as "black boxes" because of their complexity and extreme non-linearity. Future research should concentrate on creating methods to interpret the model's judgments and give therapists useful information. To draw attention to the areas of interest in the input image and comprehend the aspects that have the greatest impact on the classification result, techniques like Grad-CAM, LIME, or SHAP might be investigated.

An additional intriguing area for future research is the integration of multi-modal data. The accuracy and reliability of cancer diagnosis can be improved by using deep learning models that can efficiently use data from a variety of modalities. To successfully merge data from many modalities and utilize complementary features, fusion solutions like early fusion, late fusion, or multi-stream architectures might be examined.

In the field of an intelligent system to detect liver cancer using DCNNs, future research will concentrate on data augmentation techniques, transfer learning, model optimization, interpretability, and the integration of multimodal data. Improvements in these fields can help create techniques for the early detection and diagnosis of liver cancer that are more precise, dependable, and therapeutically valuable, ultimately enhancing patient outcomes and healthcare provision.

Another thing that we observed is that there is a need to develop a system that accepts medical images of any type like MRI, CT, PET and Ultrasound. There should also be no restrictions on the size of medical images (currently most deep learning systems accept input image of size 256*256). Images of higher size is first compressed and then given as input to system, which causes information loss. Effective image pre-processing is also required which may be able to remove any noise present in the input images.

Another important requirement is an automatic segmentation system which can automatically segment liver without much manual input. Currently liver segmentation requires lot of manual inputs. Also, it takes a lot of time in segmenting liver which is not desirable.

Finally, classification of liver cancer into exact type is required. This will help medical experts to save a lot of time and they will be able to start the medication accurately and early. This is one field where lot of research work is being done and still there is a lot of scope for future research. We can summarize some of the research statements from above discussions to be used by others for carrying out research.

- To develop an efficient system for automatic segmentation and detection of liver cancer.

- To develop an efficient system to remove noise and automatically segment medical images.
- To develop an efficient system that can accept by any medical image for automated cancer detection.

6.3 Recommendations

The following are suggestions for constructing a DCNN based intelligent system to identify liver cancer:

- **Data Collection**: Gather a sizable and varied array of liver cancer photos, including both malignant and non-cancerous samples. Make sure the dataset is representative of the various liver cancer stages and types. Standardize image sizes, get rid of noise, and properly normalize the data before processing it.
- **Model selection and architecture**: Select a CNN architecture that is appropriate and has a proven track record of success in applications requiring the classification of medical images. Considerable models include VGGNet, ResNet, InceptionNet, and EfficientNet. A pre-trained model, such ResNet-50, can be chosen to save time and money. The pre-trained model can also be improved by making adjustments specifically for liver cancer detection.
- **Transfer Learning**: Apply transfer learning by pre-training the weights of the chosen CNN model with data from a sizable image dataset. Using this method, the model can use the traits it has learned from the source domain and adapt them to the target domain (pictures of liver cancer). Improve the model's capacity to recognize cancer-specific features by fine-tuning it using the liver cancer dataset for training.
- **Data Augmentation**: Use strategies for data augmentation to expand and diversify the training dataset. The generalization and robustness of the model can be improved using methods like rotation, scaling, translation, flipping, and adding noise.
- **Transfer Strategy**: Divide the dataset into training, validation, and testing sets as part of your training strategy. Utilize the training set to train the CNN model,

then use the validation set to evaluate its results. Based on the outcomes of the validation set, alter hyper parameters such the learning rate, batch size, and optimizer. Implement early stopping to avoid over fitting, and depending on validation measures, choose the model that performs the best.

- **Measures for Evaluation**: Decide on the best measures for evaluating the model's performance. Accuracy, Sensitivity, specificity, precision, recall, F1 score are typical measures for binary classification tasks. Additionally, take into account specialized metrics for detecting liver cancer, like sensitivity and specificity.
- **Performance Optimization**: Apply strategies to improve the model's performance. To avoid over fitting, this may entail using regularization strategies like dropout or L2 regularization. Use cutting-edge optimization techniques like Adam or RMSprop to improve the convergence and effectiveness of training. To find the ideal configuration, try out various learning rates and batch sizes.
- **Interpretability and Explainability**: Include strategies to improve the predictability of the model's predictions in terms of their interpretability and explain ability. It is possible to gain knowledge about the areas of the image that are most important to the categorization choice using techniques like Grad-CAM, saliency maps, or attention mechanisms. This can make it easier for medical experts to comprehend and believe the model's outputs.
- **Clinical trials and external validation**: Use an independent dataset to carry out an external validation of the produced model. Work together with medical professionals to carry out clinical studies and assess the model's performance in actual use cases. Continually improve the system and release updates based on input from healthcare professionals.
- **Ethics**: Think about the moral ramifications of putting an intelligent system for detecting liver cancer into place. Establish privacy and data protection procedures. Put in place measures to address conceivable biases in the data or automated judgments. To foster trust and ensure appropriate deployment, engage

in open dialogue with patients, healthcare professionals, and other pertinent stakeholders.

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APPENDIX A

List of Publications

1- Siddique, M.A. and Singh, S.K. (2022) ‘A survey of computer vision-based liver cancer detection’, Int. J. Bioinformatics Research and Applications, Vol. 18, No. 6, pp.544–555. (Scopus Q4 , SJR 0.12) https://doi.org/10.1504/IJBRA.2022.129263

2- M.A., Singh, S.K. and Hasan, M. ‘Robust liver segmentation using marker controlled watershed transform’, Int. J. Medical Engineering and Informatics. (Accepted) (Scopus Q4 , SJR 0.12)

3- M. A. Siddique, S. K. Singh,M. Hasan, ‘Cancer symptoms detection from liver CT images using multistage pre-processors’, International Journal of Electrical and Electronics Research.(Accepted and Indexed)(Scopus Q4 , SJR 0.12)

4- M. A. Siddique, S. K. Singh,M. Hasan, Computer-aided liver cancer detection: A comprehensive review, Int. J. of computer vision and robotics. (Accepted) (Scopus Q4 , SJR 0.12)

5- M. A. Siddique, S. K. Singh,M. Hasan, ‘Double Stage Guassian Filtering and Marker Controlled Watershed Transform based Deep Learning Technique to automatically Detect Liver Cancer Using CT Scan Images’, International Journal of Intelligent Systems and Applications in Engineering’. (Accepted and Indexed in Scopus) (Scopus Q3 , SJR 0.23)

6- Siddique, Mohammad & Singh, Shailendra & Hasan, Moin. (2022). A Robust technique for Pre-Processing Liver CT images using Double Stage Gaussian Filtering with Texture and Contrast Enhancement. NeuroQuantology.20. 1963-1969. 10.14704/nq.2022.20.9.NQ44227.

7- Siddique, Mohammad & Singh, Shailendra & Hasan, Moin. (2022). Effective Segmentation of Liver CT images using Marker Controlled Watershed Algorithm. IEEE explore. 10.1109/ICETEMS56252.2022.10093254