Human age estimation using facial images

Dissertation II

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DECLARATION

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ABSTRACT

Age estimation is one of the methods of image classification. It can be defined as determining age of a person or age group from facial images. In this paper we try to gives an overview of recent research on facial age estimation, Along with an overview of previous research on this topic.

Some of basic age estimation models are given: anthropometric model, active appearance model, aging pattern subspace and age manifold. In this paper, we are going to propose a method to identify the Age classes of face images. This method is based on the 4 steps these are 1-Pre-processing 2-Facial feature extraction 3-Finding wrinkles and 4-Age identification**.**

Automatic age estimation has rarely been explored. Other research topics include predicting feature faces, age estimation.

However, very few studies have been done on age classification or age estimation. In this research, we try to prove that computer can estimate/classify human age according to features extracted from human facial image using SWIFT, PCA, edge detection.

In this work we develop a robust age classification within certain ranges. These ranges are classified into four groups that are child, young, and adult, old. Our approach has been developed, tested and trained using the database FG-NET. The algorithm classifies subjects into four different age categories by using the following key steps: Pre-processing, facial feature extraction, finding wrinkles and age identification**.**

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CHAPTER 1

INTRODUCTION

1.1 AGE ESTIMATION

Age estimation is an important factor in facial image classification. Age estimation is defined as study of facial features in order to know about the age of a person or a group of persons. In this study age of a person is defined based on his or hers biometric features, precisely on the basis of two-dimensional facial images. Facial characteristic points can be defined as a standard reference points on human face used by scientists in order to recognize a person's face, or in this case, to estimate the age of a person. Changes in texture of face are defined as changes in face associated with skin and muscle elasticity. The aging process affects structure and appearance of a person in many ways. The changes that occur are related to craniofacial morphology (change in study of skulls and bones of a person) and face texture. Certain features of craniofacial morphology appear only in people of certain age and change during the aging process.

1.2 TYPES OF AGES

Age estimation can be defined as a process of determining age of a person or a group. Person's age can be determined in many ways, but this research is concerned with age estimation based on two-dimensional images of human subjects.

According to Geng et al., there are several types of age:

1. Chronological age is defined as the number of years a person has lived.

2. Appearance is the information about age, defined by person's appearance.

3. Perceived age is defined by other people on the basis of a person's appearance.

4. Estimated age is the age defined by computer based on person's appearance.

Appearance age is usually very close to the actual or chronological age. The objective of age estimation is that estimated age is as close to appearance age as possible.

1.3 How age estimation is effected with growth of a person

Geng et al. in their work on the automated age estimation recognized two stages official aging.

The first phase is the early years, defined as the years from birth to adulthood. At this stage, most of the changes are caused by changes in craniofacial growth:

1. Chin becomes more prominent.
2. Cheeks are spread over a larger area.
3. Characteristics of the face increase and cover the interstices.
4. Forehead falls back, reduces the free space on the surface of the skull.

In addition to changes caused by craniofacial growth, minor changes in the skin occur :

1. Facial hair become denser and change color.
2. Skin color changes.

The second phase of the aging face, recognized by Geng et al. is during adulthood. Adulthood is defined as the time from the end of growth to old age. The main changes in this stage are changes in skin texture. Skin becomes thinner, darker, less elastic and more leathery.

Also, wrinkles, under chin, sagging cheeks and lowered bags under the eyes appear. But there is also some small craniofacial growth at this stage, mainly changes in the shape of the face, but most of the craniofacial growth occurs at an early age of the individual.

1.4 DATABASE BASED ON FACIAL IMAGES

There are a few publicly available databases which have facial images with age information. The three best known are used in many works and have already been mentioned in the related work. In the following we provide some basic description for each of them.

1.4.1 FG-NET:

The database FG-net (Face and Gesture Recognition Research Network) was built by the European work group on face and gesture recognition. The database contains on average 12 pictures of varying ages between 0 and 69, for each of its 82 subjects. Altogether there are a mixture of 1002 color and grey scale images, which were taken in totally uncontrolled environments. Each was manually annotated with 68 landmark points. In addition there is a data _le for every image, containing type, quality, size of the image and information about the subject such as age, gender, spectacles, hat, mustache, beard and pose. Some example images with landmark annotations are shown in Figure 1

Figure 1: Some images of the FG-NET database with landmarks

1.4.2 MORPH:

The database was collected by the Face Aging Group and is intended for researchers interested in face-based biometrics. The database consists of two parts Album 1 and Album2. Album 1 contains 1690 greyscale images of 631 subjects between 15 and 68 years old. For every sample there is additional information about race, gender, facial hair, glasses, age and also 4 coordinates for the position of the eyes. Album 2 consists of 55608 images of 13673 subjects between 16 and 99 years. Information about race, gender, facial hair, glasses and age is available.

1.4.3 CVL:

The Center for Vital Longevity (CVL) database was created at the University of Michigan by Meredith Minear and Denise Park. The database can be divided into three categories. First, there is a set of 308 profile images. The next category consists of 580 neutral frontal face color images and an additional 159 greyscale pictures. The last one is divided into the emotions angry, annoyed, disgusted, grumpy, happy, sad, and surprised and contains a total of 258 images. The subjects belong to different races and are in the age range of 18 to 94. The gender and the age is part of the rename.

1.5FACIAL REPRESENTATION MODELS

There are many different models for facial representation. Models recognized in are:

1. Anthropometric Model
2. Active Appearance Model
3. Aging Pattern Subspace
4. Age Manifold.

1.5.1 Anthropometric model

Facial Anthropometry is the science of measuring the size and proportions of the human face. The main idea of this model is to consult research related to craniofacial growth and development. Craniofacial research theory uses a mathematical model for description of a person's head from birth to adulthood: $\Theta' = \Theta$, $R' = R(1 + k(1-\cos\Theta))$ where Θ is the angle formed by the vertical axis, R is the radius of the circle, k is a parameter which increases with time, and (R', Θ') circuit growth over time. Farkas gave an overview of facial anthropometry. He defined facial anthropometric as measures taken from 57 characteristic points of the face taken over years . For age estimation, distances and ratios between characteristic points are commonly used, instead of using a mathematical model, because it is difficult to measure face profile on the two-dimensional face images.

Computations in this model are based on the craniofacial development theory. Changes in the appearance of face caused by the growth and texture samples are sufficient to categorize faces in several age groups. This model is suitable for a rough age estimation, but not for detailed classification. Anthropometric model is based on rations of the human face, as shown in Figure 2.

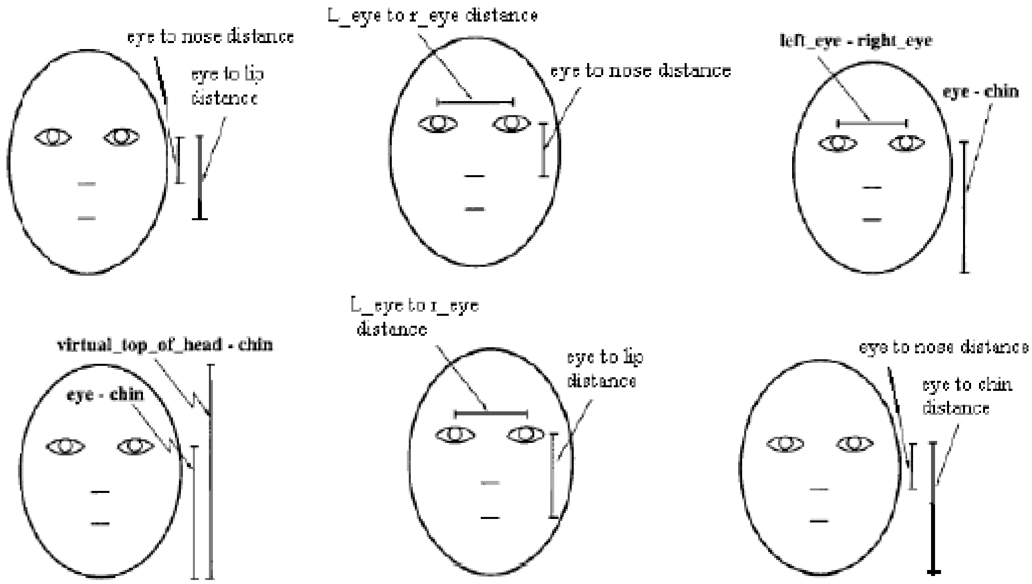


Figure 2: Ratio on human face

This model is useful for the classification of people in minors and adults, but it cannot distinguish between adults of different age, for example, young adults and seniors. This is the main reason why Kwon and Lobo used wrinkle analysis to distinguish between young adults and elderly.

Anthropometric model is useful for younger people, but not for adults. In practice, it can only be used for an face images for measuring facial geometry, because the distances and ratios are calculated from two-dimensional images of individuals that are sensitive to the positions. This model takes into account only geometry of face, without information about the texture.

1.5.2 Active appearance model

This model was proposed in 1998 by Cootes et al. using facial images; statistical shape model and intensity model are learned separately. In 2002 The AAM has been expanded to facial aging suggesting an aging function defined by age = f (b), to explain the variation in years. Age is the age of a person in the picture, b is a vector containing 50 parameters learned from AAM, and f is an aging function. The function defines the relationship between person's age and facial description parameters. There are different forms of an aging function. Some examples of such functions are: quadratic aging function, linear aging function, cubic aging function and others.

Unlike anthropometric model, AAM is not oriented only to younger people, but deals with assessment of the age of people of all ages. It works in a way that takes into consideration not only the geometry of human face, but its texture also. In this way the age of a person can be estimated more accurately.

1.5.3 Aging pattern subspace

Instead of using every face image separately aging pattern subspace model uses a sequence of facial aging images to model the aging process. This model was developed by Geng et al and named AGES (Aging pattern Subspace). Aging pattern is defined as a sequence of facial image of a person, sorted by time.

AGES works in two steps. The first step is a learning step; the second step is the age estimation step. In the first step, PCA is used to obtain the subspace representation. The difference from the standard PCA approach is that there are probably no images for each year for each aging pattern. So EM (Expectation-Maximization) is used as a method of iterative learning to minimize error in reconstruction. Error while reconstruction is defined as the difference between the available images of the face and the face reconstructed images. In the second step, the test face image needs to find a pattern of aging that suits that image, and the exact position of the year in the sample. Position year returned is the estimated age of a person in the test image.

To cope with incomplete data, due to difficulties in data collection, the aging pattern subspace models the sequence of a person's aging face images by learning subspaces. Age of the person being tested is determined by the projection in the subspace that can best reconstruct the face image. Methods based on aging functions view age estimation as a classification problem: face images are data, and the goal is the age of a person in the picture. According to aging pattern is a sequence of images sorted by age. The emphasis of this model is the use of facial images of a person at different ages to define the aging pattern.

1.5.4 Age manifold

Instead of learning the specific aging pattern for each person, it is possible to learn the common pattern of aging for more than one person at different ages. For each age, more than one facial image is used for age representation. Each person can have several face images in one age or in an age range. Therefore, this model is more flexible than AGES model, and it is much easier to collect a larger number of samples (facial images) and create a larger database. This model uses a manifold embedding technique for learning a low-dimensional aging trend for many facial images of the same age. The only requirement of this model is that the sample size for learning is large enough so that embedded manifold can be taught with statistical sufficiency.

1.5.5 Support Vector Machine

A Support Vector Machine (SVM) is a supervised learning method, which uses so called support vectors to build a model for classification or regression. The basic algorithm is described in V. Vapnik and A. Lerner's work. The aim is to find an optimal hyper plane to separate two classes. In this case optimal means that besides just providing the lowest separation error, it is also as good as possible regarding generalization. This can be illustrated with a simple example, shown in Figure 3. The line H1 separates the two classes with no error, but the margin between the point clouds and the hyperplane is very small. In contrast H2 is also a separation with no error, but provides the greatest possible margin and thus promises the best generalization.

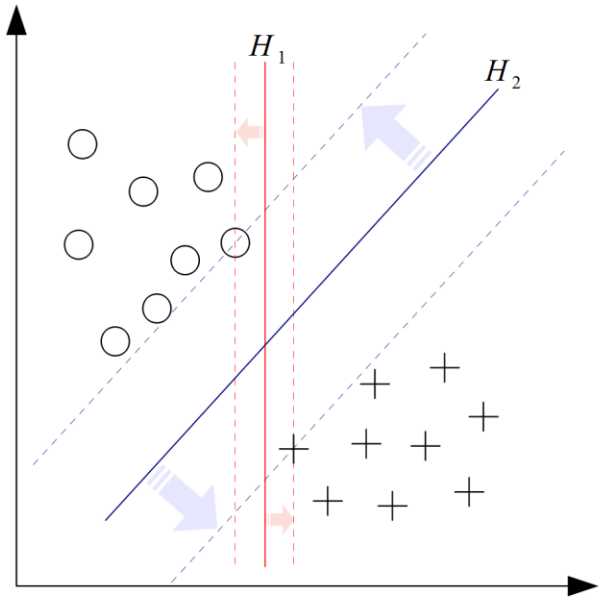


Figure 3: Example for an optimal hyperplane

CHAPTER 2

LITERATURE REVIEW

In this chapter, study of various research papers by many researchers has been done and their results has been compared.

2.1 First Attempts by Kwon and Lobo

One of the first attempts to develop facial age estimation algorithms was reported by Kwon and Lobo (Kwon 1999).

2.1.1Techinque

Kwon and Lobo use two main types of features: Geometrical ratios calculated based on the distance and the size of certain facial characteristics and an estimation of the amount of wrinkles detected by deformable contours (snakes) in facial areas where wrinkles are usually encountered. Based on these features Kwon and Lobo (Kwon 1999) classify faces into babies, adults and seniors based on a computational theory for visual age classification from facial images. First, primary features of the face, namely the eyes, nose, mouth, chin, and virtual top of the head, are found. The research in age-estimation started in 1990s and up to now, many approaches have been proposed. They typically consist of two main steps: image representation and age prediction. For the image representation, the most common models are Anthropometric model , Active Appearance Model (AAM) , aging pattern subspace, aging manifolds, and patch-based model. The final step for age estimation is either the multiclass classification problem or the regression problem. In 1999, Kwon measured the changes of face in shapes, e.g. six geometric ratios of key features, to classify faces into appropriate age groups.

2.1.2 Result

Divide into two groups only that are child and adult.

2.1.3 Limitation

Basic approach, the classification was into broad categories not in an exact manner.

2.2 Ramanathan and Dehshibi

2.2.1 Technique

Drawing inspiration from this work, Ramanathan, Dehshibi, later used the geometric ratios of facial features and added information of texture, e.g. wrinkles, in their approaches. Although these approaches achieved low Mean Absolute Errors (MAEs), they can only deal with young ages when the shapes of faces vary largely. Moreover, because of the sensitivity to head pose in the steps of computing geometric ratios in 2D face images, only frontal faces can be used.

Limitation

- Deals with young ages when the shape of faces vary largely.
- Used only frontal faces.

2.3 Lanitis and KhoaLuu

Adopting the Active Appearance Models (AAMs) approach, Lanitis et al.,KhoaLuu et al. used AAM features, which combine both shape and texture information in their age estimation studies.

2.4 Ricanek

In 2009, using AAM features extracted from image with 161 landmarks, Ricanek et al. developed a multiethnic age-estimation system that can deal with the race problem. Recently, based on the arguments that age information is often encoded by local information, such as wrinkles around the eye corners, other approaches are to divide face images into many sub-regions, extract features from these regions, and then combine them together.

2.5 Yan

Yan et al. proposed to use Spatially Flexible Patch (SFP) and Gaussian Mixture Model (GMM).

2.6 B. Ni

B. Ni et al. developed a technique to extend the human aging image dataset by mining the web resource and then used SFP for representing face images. Suo et al.designed a multiresolution hierarchical graphical face model for age estimation. LBP features and Gabor features are also exploited in the work of Günay , and Gao .

2.7 Guo

Guo et al., in 2009, investigated the biologically inspired feature (BIF) derived from a feed forward model of the primate visual object recognition pathway – HMAX model. The advantages are that small translations. The proposed approach to identify the age range algorithm that is free from previous disadvantages. The proposed method classifies face images into one of four well-ordered age groups range, which contains four key steps, pre-processing, facial feature extraction, wrinkle analysis, age range identification

Changes in skin texture usually occur in adulthood. There have been many research on craniofacial morphology of individuals from different aspects. One of these studies is the one conducted by Patterson et al. They propose using aging function based on AAM (Active Appearance Model), which is based on the use of PCA (Principal Component Analysis) method.

2.8 Kwon and Lobo

2.8.1 Technique

In 1994. Kwon and Lobo proposed theory and practical calculation for age classification of face images. Their calculations are based on craniofacial morphology and wrinkle analysis. Geng et al. presented the AGES (Aging Pattern Subspace) method for age estimation. The basic idea is to model the aging pattern, which is defined as a sequence of images sorted in time order, by constructing a representative subspace. The proper aging pattern for a previously unseen face is determined by the projection in the subspace that can reconstruct the face image with minimum error, while the position of the face image in that aging pattern indicates age.

2.8.2 Limitation

There are some problems in age estimation, and one of those problems is ethics of age estimation, especially in age estimation of children. Existing methods, such as skeletal and dental age estimation are invasive and according to European Council Directive 97 ⁄ 43 ⁄Euratom people have the legal right to object a medical age estimation. In a study of alternative reception arrangements at the port of Dover in England, unaccompanied children were placed under the care of the Social Service Department for a period of 7 days, during which the age assessment was carried out. In subsequent interviews, the children expressed annoyance of having participated in a process that they did not understand and which they experienced as hostile.

2.9 Fares Alnajar, Caifeng Shan, Theo Gevers and Jan-Mark Geusebroek, July 2012

Has proposed a system which adopts a learning-based encoding method for age estimation under unconstrained imaging condition. There has been similar work done for face recognition in real life face images. They propose an approach to extract robust and discriminative facial features & use soft encoding. Then coding is done by assigning each pixel to one of the multiple candidate code. And then the last step is to plot orientation histogram of local gradients.

Patch-based code learning is basically code set is learned from the whole face using the sampled vectors. From the sampled vector, a histogram is created. Once all the histogram is been created, they are all concatenated to form a global descriptor. Each human face is different, each of them has a different pattern, color and patched.

Each individual can a different codes for a patch, consider an example like in a certain patch some of the code may appear in majority while for another patch the same set of codes are rare to be found. To illustrate this point they performed a certain experiment in which they took data set of 2000+ images and developed 2 code set from those images. Later when they extracted the sample vector from those images using these 2 code sets and constructed histogram of the same. The histogram is as follows –

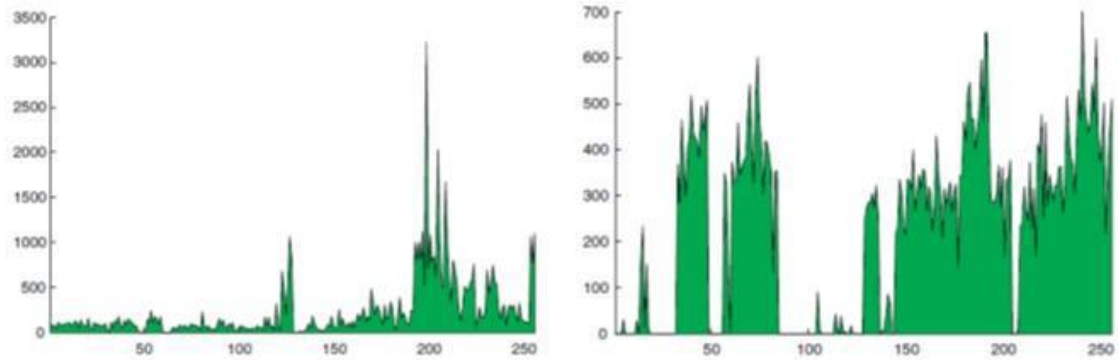


Figure 4 : shows the 2 histogram created using the sample vectors using the two code set over the 2000+ images dataset.

Soft Encoding is the input image with the learned codebook, each sampled vector (at each pixel) is assigned to the closest code. This is known as Hard Coding. Soften coding is used in image classification. In real world, for facial image, ambiguities will exists. In simple terms, consider a given sample vector, there is a possibility where there are more than one candidate codes. The assignment of code which is closest becomes difficult as the encoding becomes sensitive to image noise and varying conditions. These factors distort the sampled vector, which result indifferent code assignment. Hence to avoid this problem they have used the soft encoding assignment schemes which assigns the given sample vector to multiple codes with weights. Soft encoding is used in image classification.

2.10 GuodongGuo, Yun Fu, Charles R. Dyer, and Thomas S. Huang in July 2008

Introduced the new learning scheme based on age manifold learning for extracting age along with other facial features. It also designs a locally adjusted robust regression for estimating ages of the human in question. The authors also claim that this approach increases the accuracy of age estimation by significant number as compared to previous methods. Basically, there are 3 main categories that can classify most existing age estimation methods. These are anthropometric model, age regression, and aging pattern subspace. The facial skin wrinkle analysis is basically used to create the anthropometric model. The face can be categorized into various age groups by the changes in the face shape, texture pattern related to growth and many other such factors. But the problem is this method is most suitable or convenient for young people, However they are not designed for refined age estimation and classification.

The first step includes detecting and cropping the face part from the entire image, this process is known as face detection. Here we collect a large number of images from different age group and test accordingly. Now in this step, we take the cropped face patch from the previous step and the perform normalization which includes geometric alignments and illumination normalization. This is basically histogram equalization. Age Manifold is used to learn to map the face image into a low dimension. Basically we transform the face image into a sub space which is of low dimension. This is now provided as the input to the next stage Robust Regression function. In Robust Regression, basically a function which is developed is applied to the Age Manifold data. This function simply does the function of fitting the Age Manifold data. In other words function is applied to fit the Age Manifold data. The last step in the process is local adjustment. The adjustment is done of the result of regression which is generated in the previous step. This step is performed to refine the local fitting of the data. So we can describe the working in short using an example. Consider a face image; the face image goes through the process of face detection followed by face normalization. After normalization, the normalized face image is projection the Age Manifold learning which has been already computed earlier during learning stage. Than after Manifold learning comes the final step where actual age of the face image is predicted using robust regression function.

2.11 Chin-Teng Lin, Dong-Lin Li, Jian-Hao Lai, Ming-Feng Han and Jyh-Yeong Chang, 29 Aug 2012

Introduced a novel and reliable framework is proposed for automatic age estimation. The age estimation is based on computer vision. Additionally, the proposed system can extract features from face image and estimate the age of the same in real time. So this unique feature has more potential in various application as compared to traditional semiautomatic systems. The result generated from this novel approach could be widely used as a real world application in various domains.

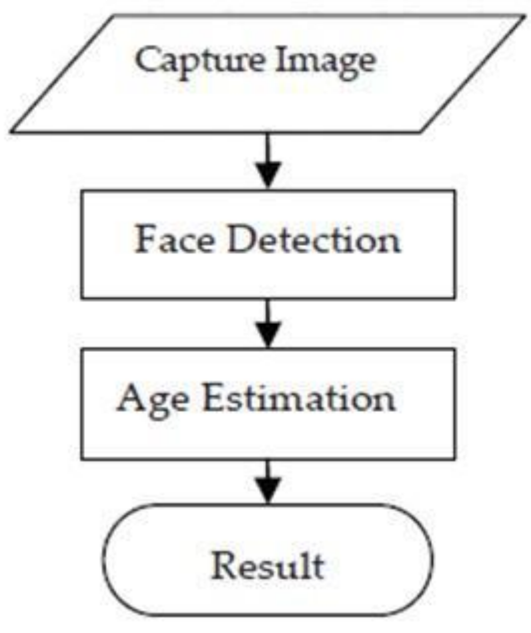


Figure 5: System Overview

The figure 5 shows the basic and simple age estimation model along with basic step to achieve the same. The system proposed in this paper consists of 2major parts or modules. Face

Detection and Age Estimation. We will see these 2 modules in details. Face Detection localizes the facial region in the image. Here different size of window is applied to the image. The basic aim of doing so is to search the multi-scale facial candidates due to the distance between the camera and the object or person in question. There are basically 12 block searching windows of different size, as mentioned earlier these window search for multi-scale purpose and the size of windows ranges from smallest (24x24) with scaling factor of 1.25. The first step in Face Detection is lighting

Normalization, which is based on histogram method. The main aim of histogram fitting method is to convert or transform the H(l) {original histogram} to G(l) {result or target histogram}. The G(l) is estimated as the histogram of the image closest to the mean value which is present in the face database.

$MH \rightarrow G(l) = MU \rightarrow G(MH \rightarrow U(l))$ (1)

Where $MH \rightarrow U(l)$ and $MH \rightarrow G(l)$ are basic histogram mapping or they can also be called as the inverse mapping from H(l) and G(l) which transforms the histogram into uniform distribution respectively.

In this paper the intensity based feature that is employed were based on Haar features. There are basically four type's rectangular features. The four features are the vertical edge, horizontal edge, vertical line and last diagonal edge.

The feature can be define by –valve subtracted= f(x,y,w,h,type)

Where (x, y) is the origin of coordinate of rectangular feature inside the search window. The w and h states the width and height of rectangular feature respectively. Type denotes the type of rectangular feature to be used and valve subtracted is basically the difference between the sum of pixel in white rectangle and sum of pixels in the dark rectangle. Rectangular feature which separates the face and non-face samples can be considered as the weak classifier. The weak classifier is denoted by $h(x, f, p, \theta)$and it is given by equation –

$h(x, f, p, \theta) = 1$, if $pf(x) < p\theta$ (3)= 0, otherwise

During face detection, there is normally a case where more than one face candidate is detected even if there is exactly one face in the image. To avoid this problem we use Region Based Clustering.

CHAPTER 3

PROPOSED METHODOLOGY

In this methodology we used four basic steps:

1-Pre-processing
2-Facialfeatures
3-Wrinkelextraction
4-Age estimation

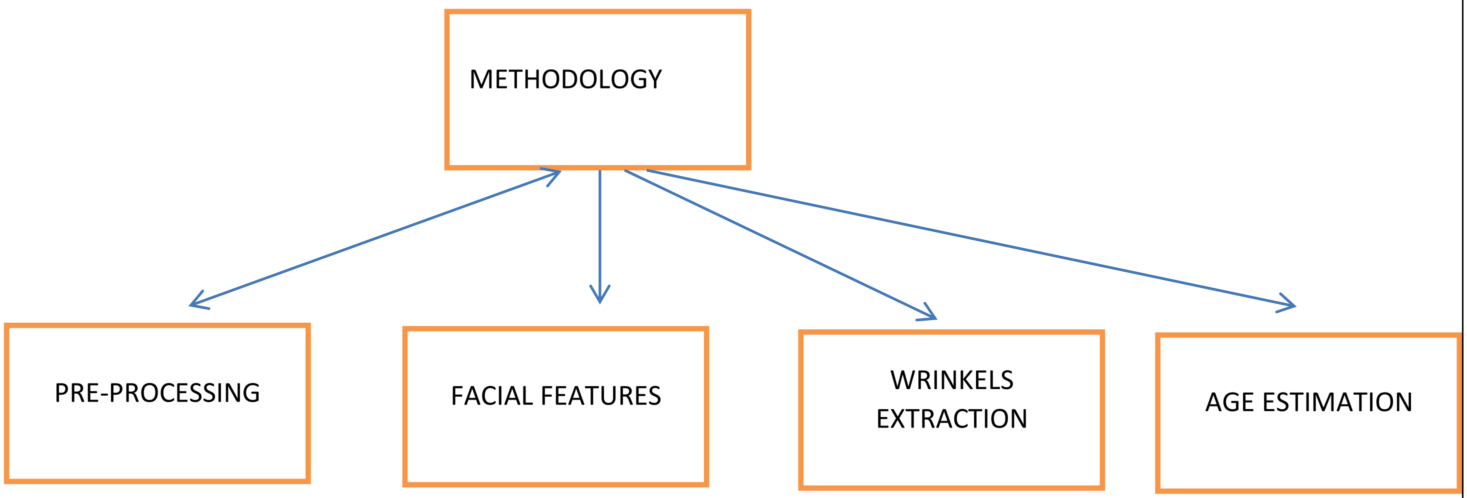


Figure 4: Methodology

3.1 Pre-processing

Image Processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photograph or video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Images are also processed as three-dimensional signals where the third-dimension being time or the z-axis.

Image processing usually refers to digital image processing, but optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The *acquisition* of images (producing the input image in the first place) is referred to as imaging.

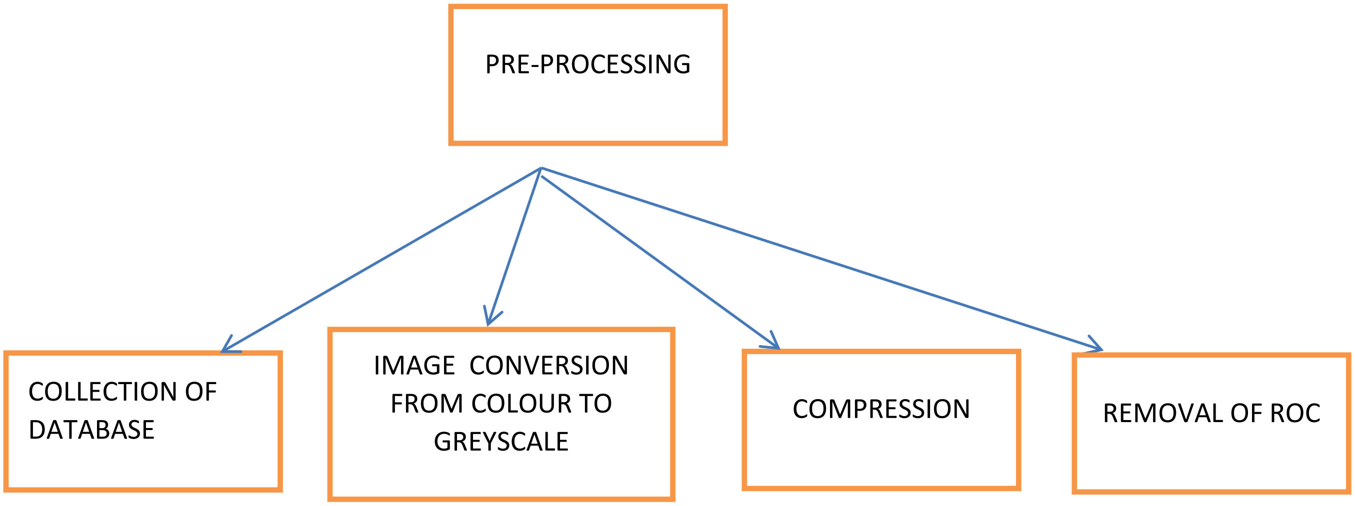


Figure 5 :Pre processing

Figure 6: Original Image

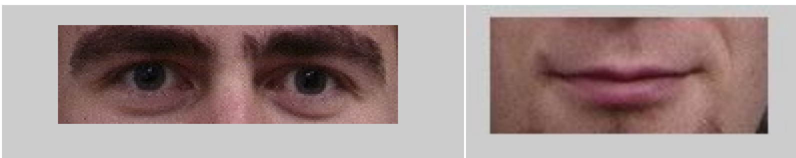


Figure 7: Cropped Image

3.2 Feature extraction

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over fit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

In this report we used sift method to perform pre- processing and used pca method to tell about features.

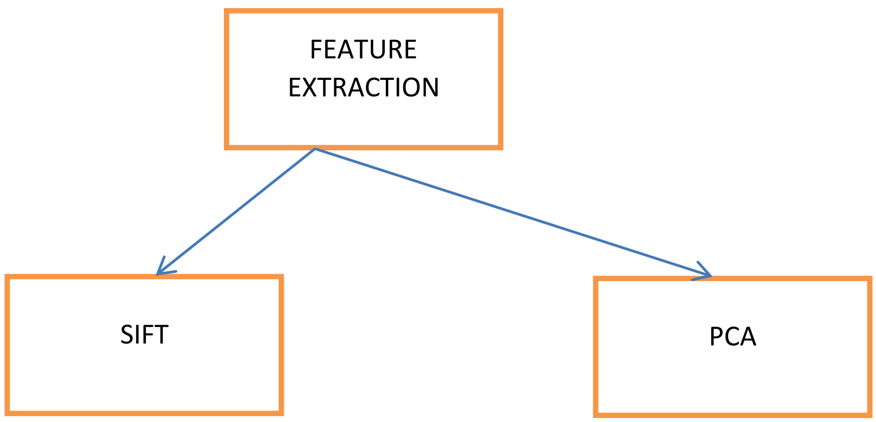


Figure 8: Feature Extraction

3.2.1 SIFT:

Scale-invariant feature transform (**SIFT**) is an algorithm in computer vision to detect and describe local features in images. The algorithm was patented in the US by the University of British Columbia and published by David Lowe in 1999.

Applications include object recognition, robotic mapping and navigation, image stitching, 3D modeling, gesture recognition, video tracking, individual identification of wildlife and match moving.

SIFT key points of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of key points that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalized Hough transform. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is computed, given the accuracy of fit and number of probable false matches. Object matches that pass all these tests can be identified as correct with high confidence.[3]

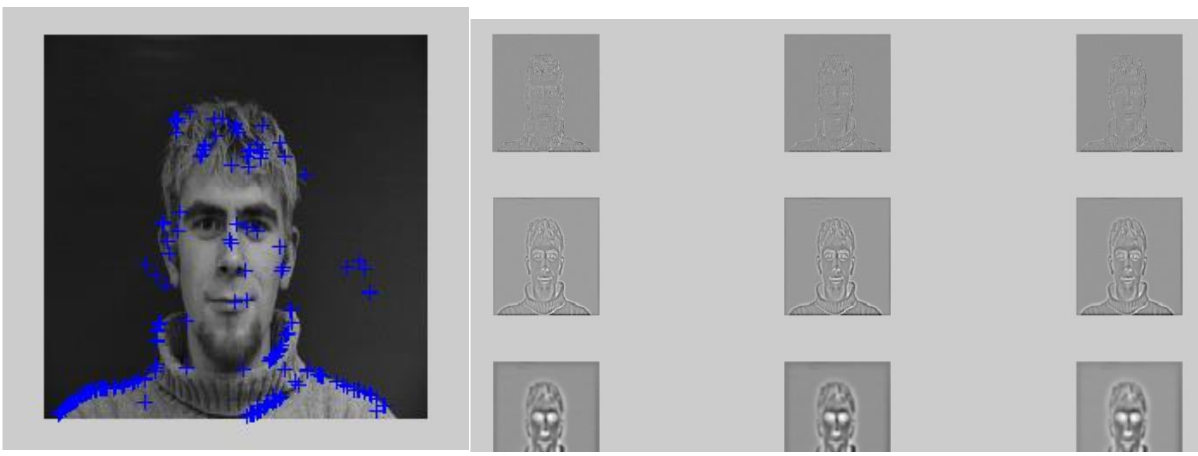


Figure 9: SIFT application

3.2.2 PCA:

Principal component analysis (**PCA**) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called **principal components**. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. The resulting vectors are an uncorrelated orthogonal basis set. PCA is sensitive to the relative scaling of the original variables.

3.3 WRINKEL EXTRACTION

In this step we try to find out wrinkles on human face by edge detection method.

3.4 AGE ESTIMATION

With the help of extracted facial wrinkles and other facial features we could classify our images into different groups

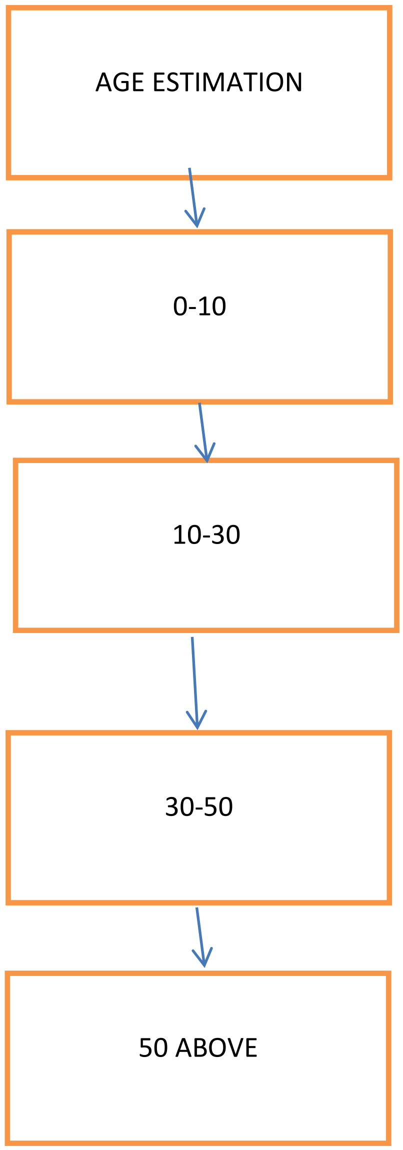


Figure 10 :Age estimation

CHAPTER 4

Core system module

Age estimation accuracy depends on how well the input images have been represented be good general discriminative features. The types of classification we use make a difference in result of age estimation for different inputs. In this chapter, we would give the complete process or framework of system and would describe each and every component also. The output of process is accurate age of an unknown image.

Core system module is the first and tree of our three modulated system ,this is considered as an most important part of our entire system .the major components which we would use in this module are :

(1)First part is to automatically take input image and detecting the face portion using BB method (2) second is to automatically find out the areas where we encounter wrinkles like forehead, near eye portion and near nose above the lip portion. (3) Third thing is to the selected area cropped out and the edge of the area need to be found out using edge detection method. (4) Final step is to count no of edge pixels and sum up them to give a total no of wrinkles a person has.

4.1 System structure

The proposed algorithm for age estimation is divided into five steps. First the image is taken and face portion is detected leaving other unwanted background this is done with the help of BB face detection method . The image is cropped from the fixed points of the face which was generated with the helps of BB that is bounding box .Then , the cropped image undergoes some sort of preprocessing techniques like resizing , gray scaling to make it binaries etc.

This image is then used to detect the area of portion responsible for more wrinkle encounter using BB again, these portion are then cropped out from the image and taken for edge detection to find out no of edge pixels present in the image which is summed up to give to give final output that represented number of wrinkle lines present on an person face. Finally this database is given for classification as an training module and tested on different images, and made a age estimator .The complete framework is illustrated in figure 11

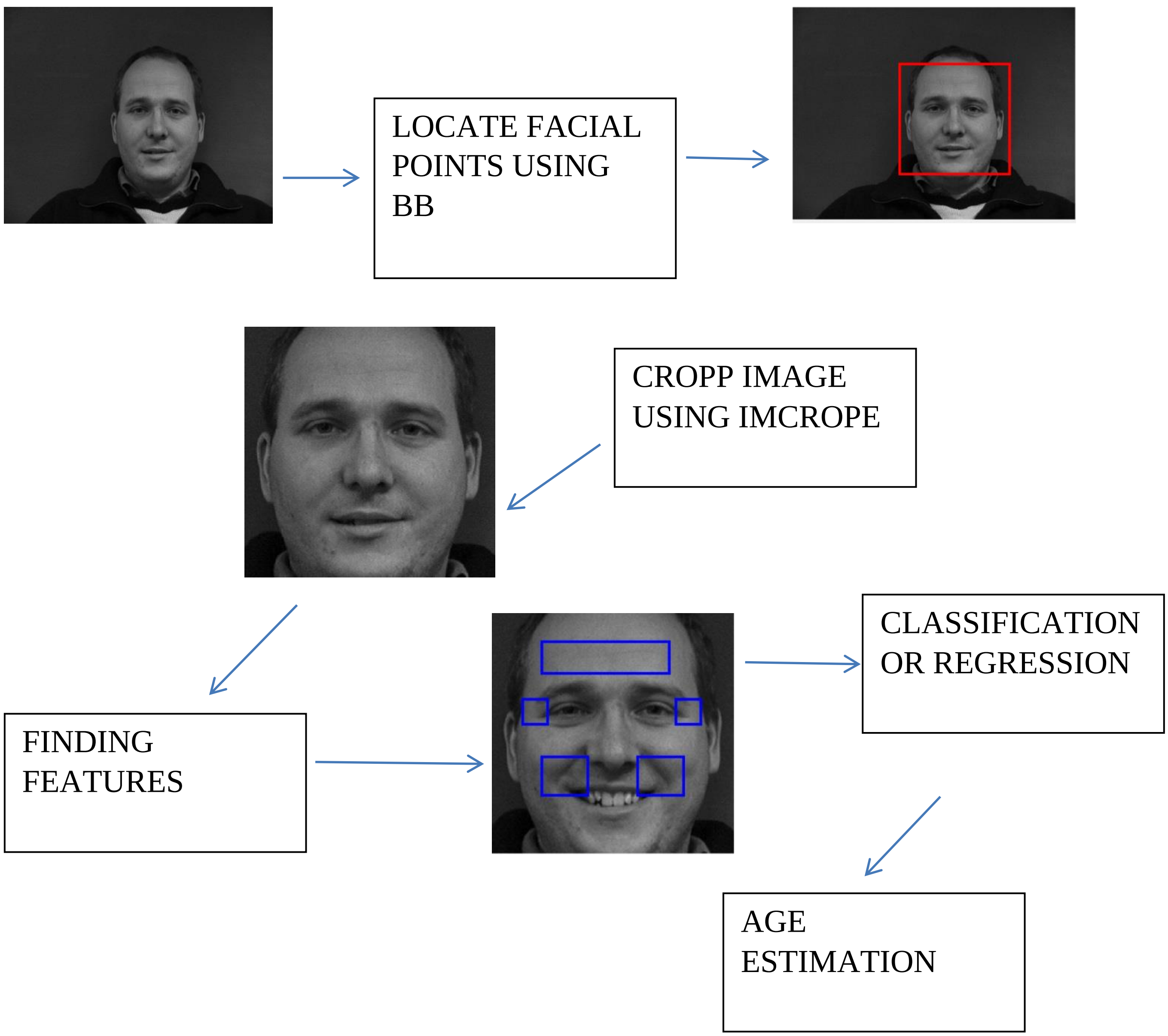


Figure 11: The complete framework

4.2 Detailed implementation

4.2.1 Face detection

Face images can demonstrate a wide range of variation in both shape and texture. Appearance variations are caused by individual differences, the deformation of an individual face due to changes in expression, pose and speaking, as well as lighting variations. Figure 12 shows how the image of a person varies with different poses. Figure 13 shows illumination changes caused by light sources at arbitrary positions and intensities that contribute to a significant amount of variability.

Figure 12 : Image of the same person with different head pose

Figure 13: Images of the different person with front pose

In this step, we aim at accurately detecting facial region to extract features only from the relevant parts of the input image. The detection part was performed using BB method. In this work, we explore the use of bounding box and inbuilt face detection nose detection eyes detection and detection of different parts of face which has multiple uses in future demand, the face detection should be such a clear process that it could detect face region for any provided input.

Figure 14: Detection of face from background

We successfully detected the face region from an image and cropped it out from the background to get an clear view and take it as input to get our features which we require for our wrinkle detection and other processing. Figure 14 shows cropped images of same person with different pose and Figure 15 shows cropped image of frontal image only.

4.3 Region of concern detection

In this we select the region that we are concerned with such as region of forehead were we found wrinkles and portion around eyes and nose above the lips , these area are bounded by box using BB method and cropped for figure out number of wrinkle lines presented in the given area for better classification of our problem because wrinkles are defined as a basic classification for age of an person .

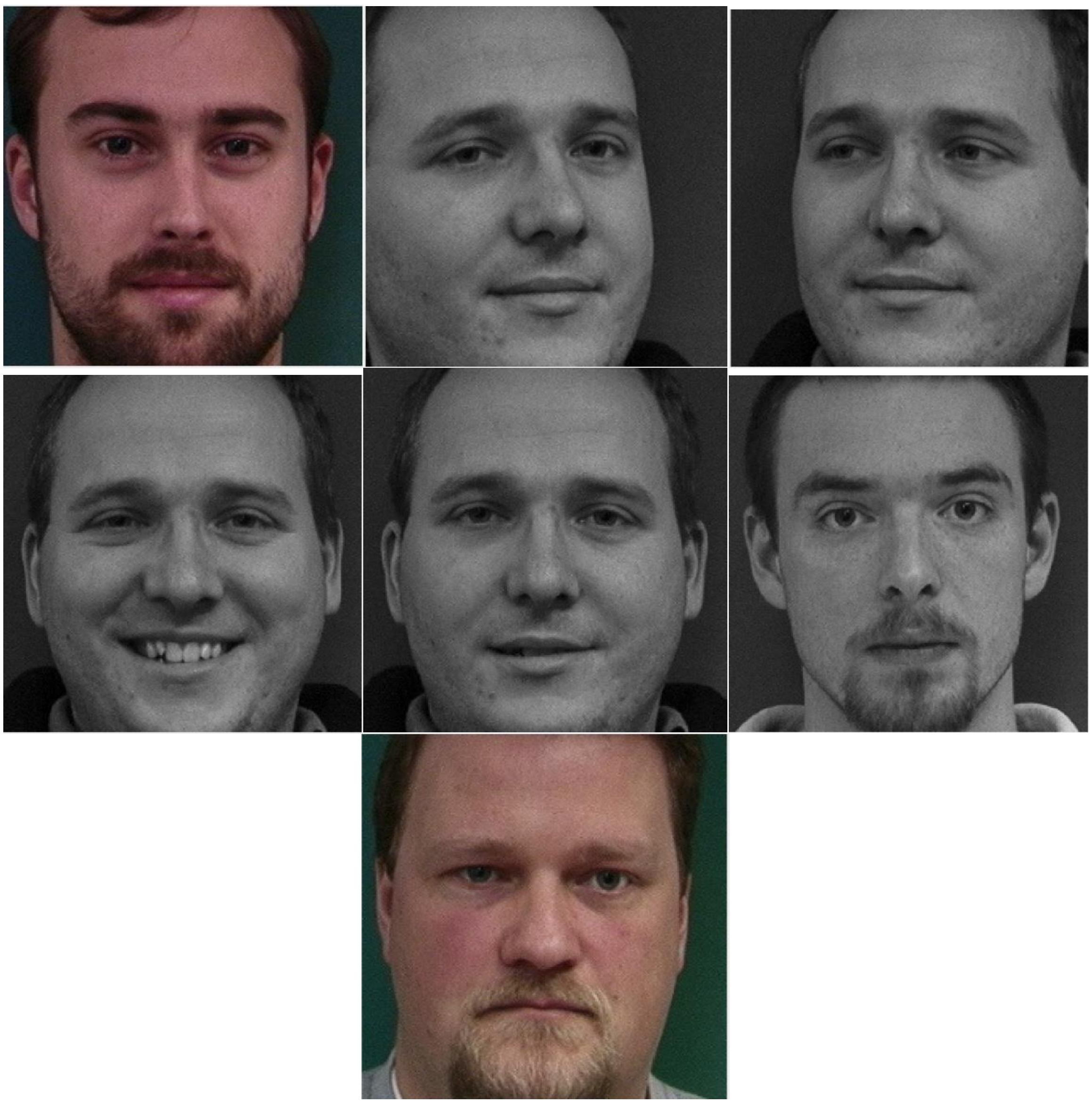
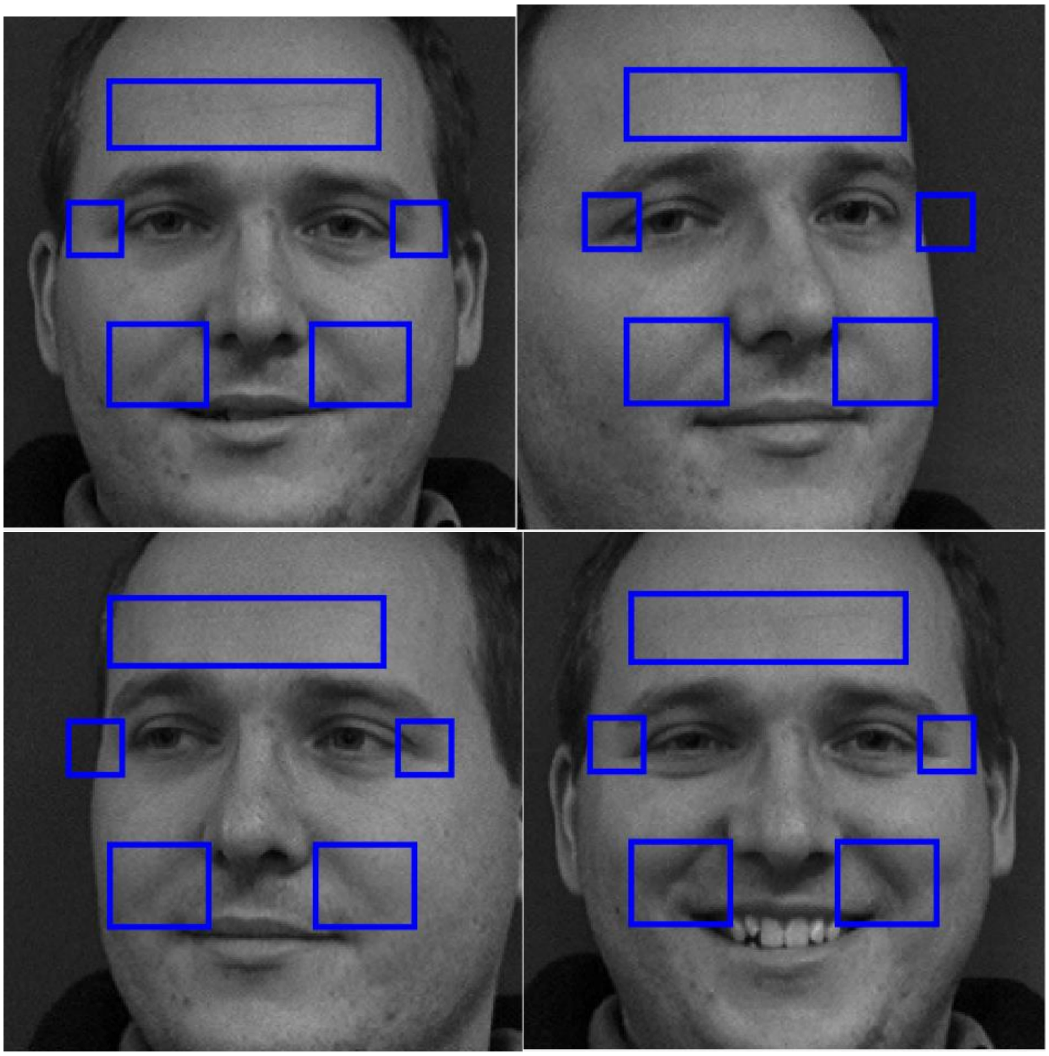


Figure 15 shows the different area for which we are concerned and it also shows its cropped image which would help us to determine our feature extraction problem .Now we would take this cropped image as input and do edge detection on it .

Edge detection is a way to find out the number of wrinkles or edges present on an given area or image. We do edge detection and get an edged image of the cropped portion, which would help me in counting number of wrinkles in the face of a person. Figure 16 show the region of concern.



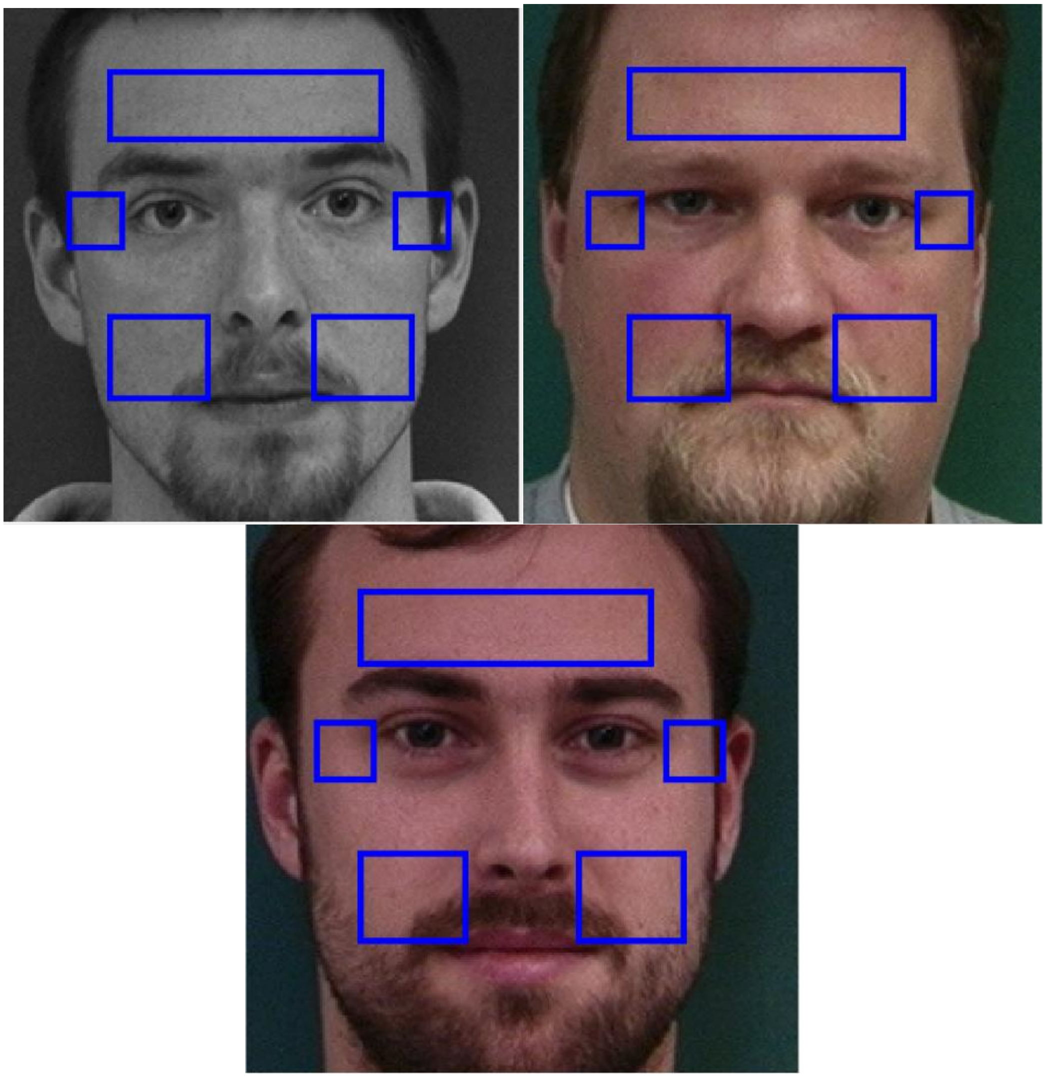


Figure 16: Edge detection of the area for which we are concerned

These wrinkles are taken as Features which would be given as input to the classifier to divide it into different categories based on their number of wrinkles. In total we had made a set of 6 such Features .

These features are :

1-F1-feature one describes the number of pixels present in forehead portion.

2-F2-feature one describes the number of pixels present in left eye portion.

3-F3-feature one describes the number of pixels present in right eye portion.

4-F4-feature one describes the number of pixels present in left side of lips portion.

5-F5-feature one describes the number of pixels present in right side of lips portion.

6-F6-feature one describes the total number of pixels present in total.

IMAGE	FEATURE 1-F1	FEATURE 2-F2	FEATURE 3-F3	FEATURE 4-F4	FEATURE 5-F5	FEATURE 6-F6
1	forehead	right eye	left side	right side of lips	left side of lips	total number of pixels
2	forehead	right eye	left side	right side of lips	left side of lips	total number of pixels
3	forehead	right eye	left side	right side of lips	left side of lips	total number of pixels

Table 1: Shows the repesentaion of different features in databse

No. of images taken as input	No. of pixel present in forehead region	No. of pixel present in right sided of eye region	No. of pixel present in left side of eye region	No. of pixel present in right side of lip region	No. of pixel present in left side of lip region	Total No. of pixels present
1	59	77	276	71	71	513
2	187	90	675	70	70	1063
3	195	18	298	49	49	610
4	165	135	646	36	36	1043
5	33	102	148	51	51	391
6	218	77	202	25	25	610
7	120	162	359	51	51	727
8	63	100	86	80	80	406
9	89	111	225	30	30	503
10	158	137	123	126	126	611

Table 2: Represent the actual value we got as output from our experiment as different features.

After extraction of all this features we finally take all this as an input to the classifier and train our network on the basis of that and based on that classification and training we test our new image on which category the new image lie this tell the accurate age of the person based on that we find the accuracy of classifier.

4.4 Classification and Regression

Age estimation can be treated as a classification problem, when each age is considered as a class label. Alternatively, age estimation can be treated as a Regression problem, where each age is considered a regression value.

We used different classification method to get proper accuracy of the system, based on different classifier there is an impact on the result of our age prediction. We used different classifiers such as SVM, ANN, KNN these are some of the classifier we used.

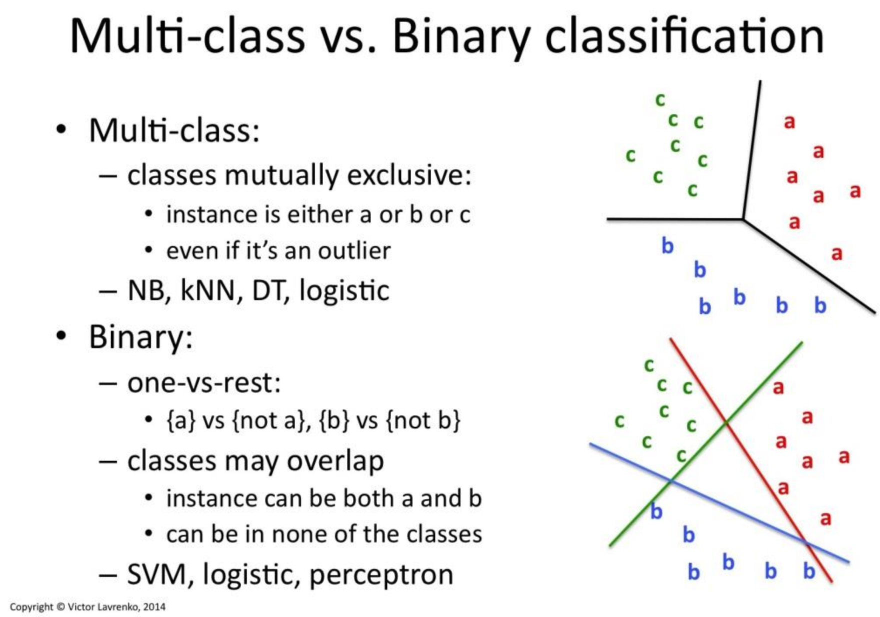


Figure 17: Binary and Multiclass Classification

For different way of classification we have different classification methods in the same way for classifying into different class we have different classification such as binary classification for 2 class and multiclass for more then 2 class. This is well explained by Figure 17

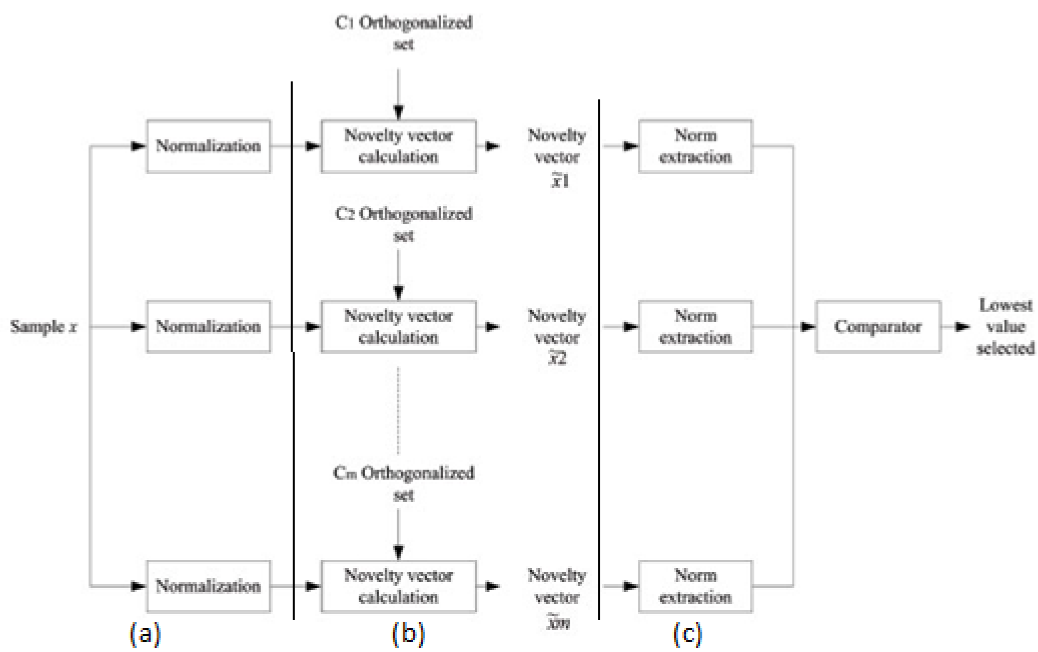


Figure 18: (a) Training the novelty filter; (b) Binary classifier using the novelty filter; (c) Multiclass classifier using novelty filters.

This is how we classify our training set into different classes by using SVM classifier above id the flow chart for that , In matlab we use given below code to train , classify and test our data.

```
trainingFeatures(i,:)=BB(img);
trainingname(i,:)=i;
```

used for training the set of images using database created with taking 7 features from different portion of face.

```
classifier=fitcecoc(trainingFeatures,trainingname);
```

used to classify the training set and its name into different classes with help of error free classifier of SVM multiclass classification ,this provides a classified list elements

```
testFeatures=extractFeature(I);
predictedLabels=predict(classifier,testFeatures);
disp(predictedLabels);
```

and the above is used to predict the given test image to different class according to the given classifier which is made by using training set matrix.
The below is the graphical representation of how different classes are divided using SVM

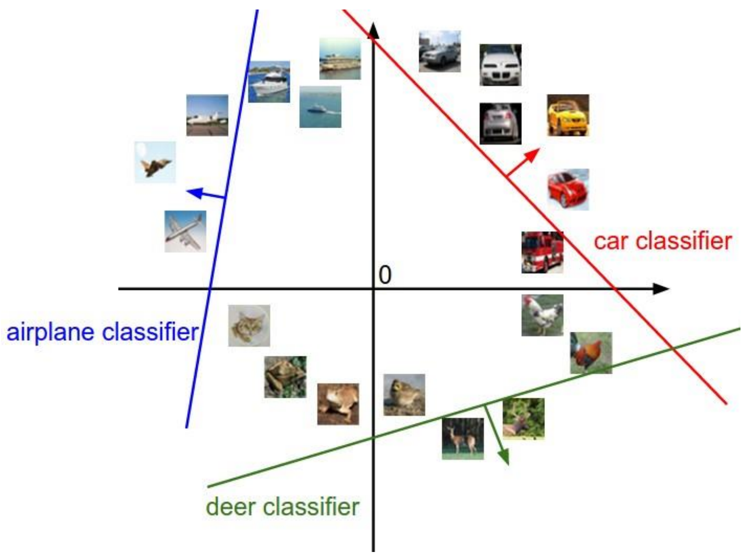


Figure 19: Graphical representation of how different classes are divided using SVM.

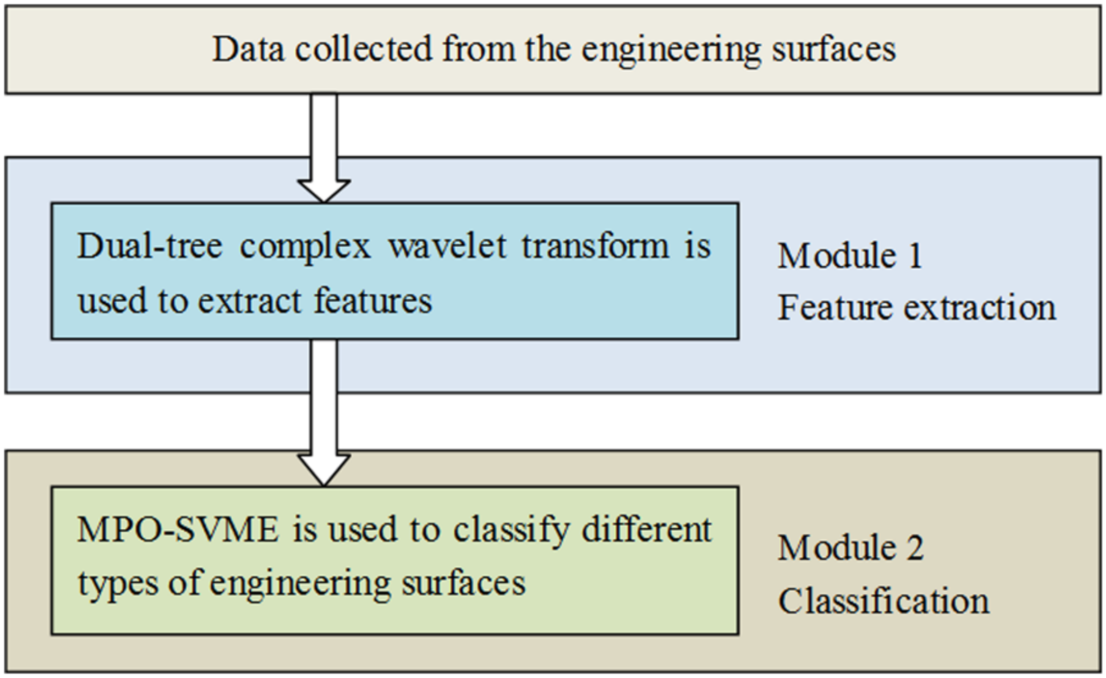


Figure 20: Represents different modules of SVM classifier

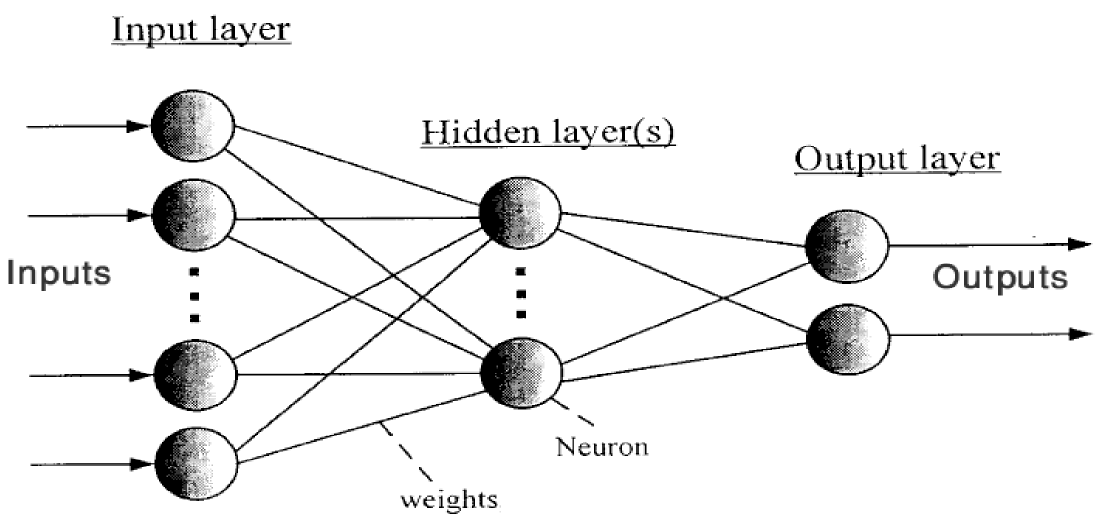


Figure 21: Represents different layers of NN (Neural Network)

The above define the neural network classifier that can be used it take different weight input process it using set of hidden layer and then let you an output which can be again minimized to a minimum error using feedback method.

Facial features are used in this part to get of classifier trained and testing. We made a database for our set of training database with n rows and 6 columns, in which we have n as number of images present in training database and 6 column represent the 6 extracted features that are F1,F2,F3,F4,F5,F5 and this database is used for training .

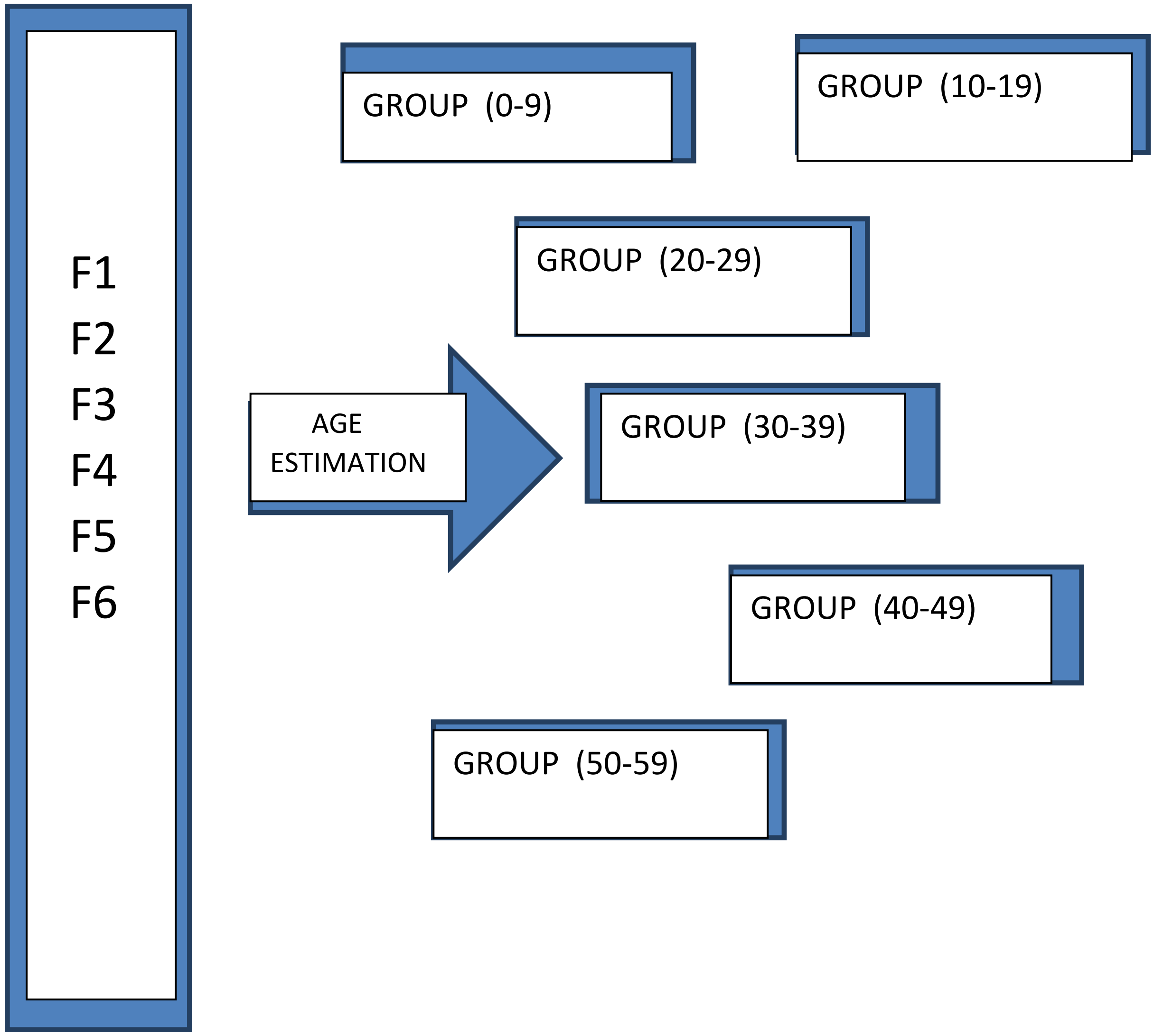


Figure 22: Represent the framework of age estimation.

4.5 Experimental Results And Conclusion

A Leave-On-Person-Out (LOPO) test strategy is used on the FG-NET database, ie., in each fold, the image of one person are used as the test set those of the others are used as the training set. After 82 folds, each subject has been used as test set once, and the final results are calculated based on all the estimations. In this way, the algorithms are tested in the case similar to real applications, ie, the subject for whom the algorithm attempts to estimate his/her age is previously unseen in the training set. In order to further test the generalization ability, the algorithm trained on the FG-NET ageing database is then tested on MORPH database.

No. of images taken as input	No. of pixel present in forehead region	No. of pixel present in right sided of eye region	No. of pixel present in left side of eye region	No. of pixel present in right side of lip region	No. of pixel present in left side of lip region	Total No. of pixels present
1	59	77	276	71	71	513
2	187	90	675	70	70	1063
3	195	18	298	49	49	610
4	165	135	646	36	36	1043
5	33	102	148	51	51	391
6	218	77	202	25	25	610
7	120	162	359	51	51	727
8	63	100	86	80	80	406
9	89	111	225	30	30	503
10	158	137	123	126	126	611

Table 3: Represents the experiment results of 10 images

This is the table of predicted feature values for first 10 training images where rows define number of images taken and column 1 defines number of wrinkles present on forehead, column 2 defines number of wrinkles present on right eye, column 3 defines number of wrinkles present on left eye, column 4 defines number of wrinkles present on right lip, column 5 defines number of wrinkles present on left lip, column 6 defines total number of wrinkles present.

Most of the age estimation framework used the entire image of the person to get the accurate age of a person they do so in order to calculate the geometric ratio of the person which can be taken through 75 feature point shapes that are present on the outer part of the face. In our research we didn't used these 75 features rather we calculated our own features which are taken as training base for calculation.

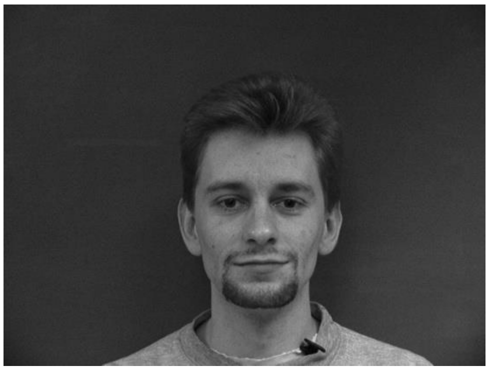



Image 1 Image 2

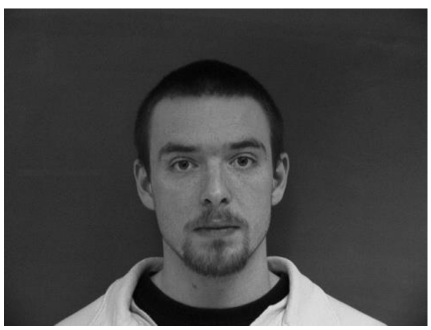



Image 3 Image 4

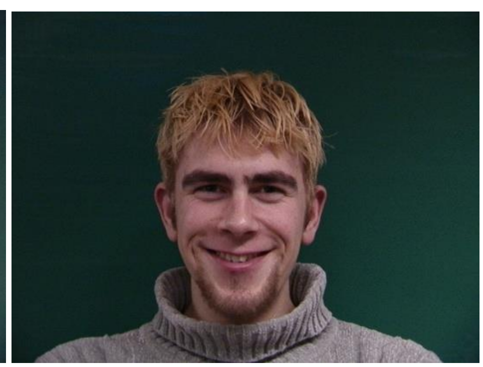



Image 5 Image 6

Figure 23: Represents the input test images

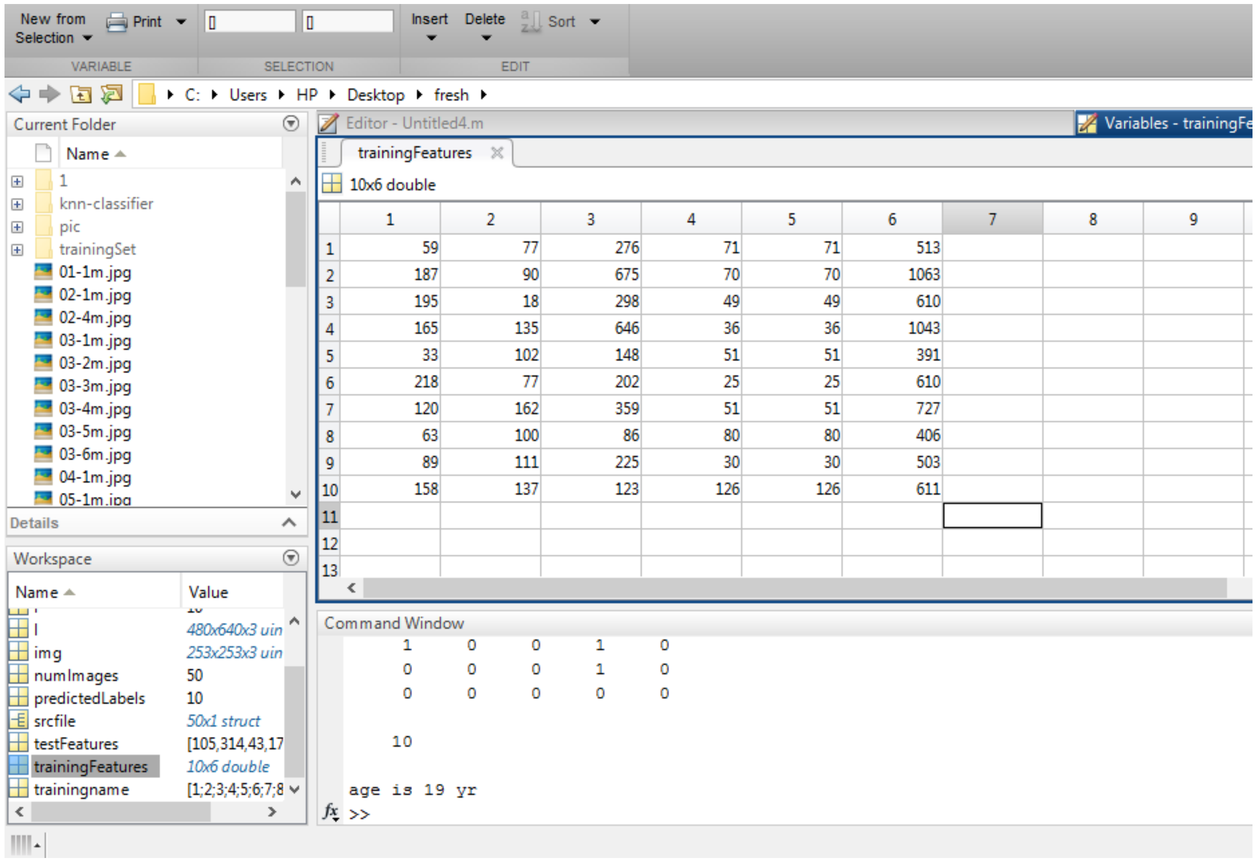
this image is taken as test image to find out the age of the person, same seven features of this images are also taken and it is compared with the matrix formed by the training set , after going through entire process the predicted age of the person is formed as:

No. of images taken as input	No. of pixel present in forehead region	No. of pixel present in right sided of eye region	No. of pixel present in left sided of eye region	No. of pixel present in right side of lip region	No. of pixel present in left side of lip region	Total No. of pixels present	Actual age of image	Predicted age of image
1	164	243	353	85	85	923	20	19
2	120	162	359	51	51	727	27	20
3	311	297	340	80	80	1083	17	13
4	75	226	98	121	121	566	30	22
5	218	121	817	74	74	1309	20	18
6	88	73	97	123	123	461	18	16

Table 4: Represent the features obtain from these 6 test images.

No of input image	Accuracy calculated
1	95%
2	74%
3	77%
4	74%
5	90%
6	89%

Table 6: Represents accuracy of the input images.



As you can see the age predicted is 19 years and actual age of the person is 20, so this proves that the accuracy of our experiment is 70-95 percentages.

Experiment result revealed that the area around eye proved to be the most significant for age estimation. The model revealed that this portion has large no of edge pixels which are the base of our experiment .The analysis shows that the eye wrinkle, which covers 30% of the facial area, contain the most important ageing features compared to internal face and whole face.

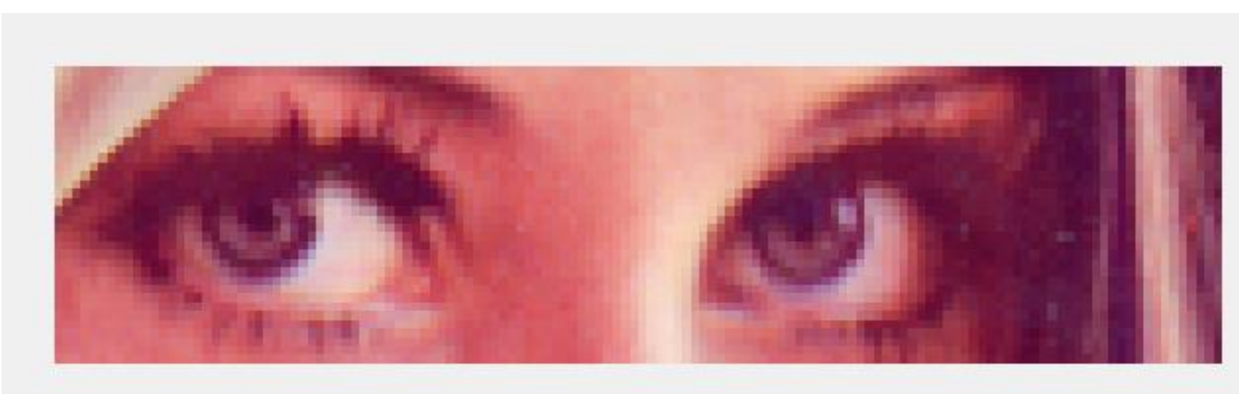


Figure 25: Represent that our experiment predict large number of wrinkles around eye region.

No. of images taken as input	No. of pixel present in forehead region	No. of pixel present in right sided of eye region	No. of pixel present in left sided of eye region	No. of pixel present in right side of lip region	No. of pixel present in left side of lip region	Total No. of pixels present
1	164	243	353	85	85	923
2	120	162	359	51	51	727
3	311	297	340	80	80	1083
4	75	226	98	121	121	566
5	218	121	817	74	74	1309
6	88	73	97	123	123	461

Table 4: Represent the features obtain from these 6 test images.

As you can see the eye whether it is life or right has large number of wrinkles present in them this is well shown by the above data.

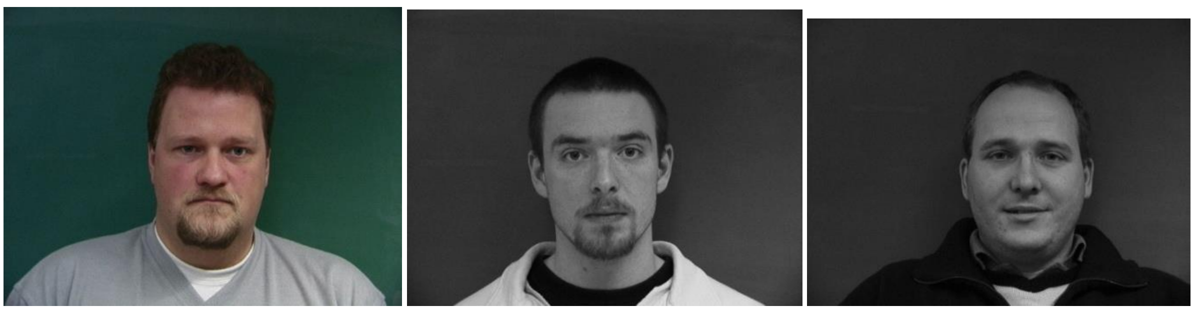
Figure 26: Represents the age estimation done in base paper H. Han, C , Otto, X, Liu and A.K.Jain

True: 20 Est. 19

True: 20 Est. 18

True: 18 Est. 16

(a)



True: 27 Est. 20

True: 17 Est. 13

True: 30 Est. 22

(b)

Figure 27: (a) Good age estimation (b) Bad age estimation

This revel that according to Figure 26 and 27 we came to know that according to my base paper my good estimation is not 100 percentage accurate but my bad estimation is better than that of base paper

CHAPTER-5
CONCLUSION

Thus it has been tried to address all the advanced and novel techniques that have been used in the area of demographic information estimation**.** The approaches used to classify age are broadly gait-based, body-based and face-based. Most of the researchers focus to classify gender using face images. But advancements in machine learning and computer vision have made it possible to do the same using full body images and even with images having partial information. Some of the significant problems which are still facing by the researchers are facial variations like occlusions, expression changes, pose variations illumination and intensity effects, computational time and high dimensionality. Working on pixels to classify age is more computationally expensive so researchers prefer to extract face features rather than direct work on pixels. Feature-based methods are categories into two i.e. global feature and local features. It is concluded that in the classification step, support vector machine is performing well as compared to other classifier algorithms. Similarly, on the other hand classification accuracy rate is also enhanced by combining different classifiers called ensemble classifiers. To overcome the facial variation problems occurred, most of the researchers have first performed some pre-processing steps on the face and body data sets like face alignment and face detection etc. Highlighting the weakness of up-to-date techniques is the main emphasis of this literary work, which will help the researchers to continue their works in this concern.

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