Age-Group Prediction of Facial Images using different Classifiers

Thesis submitted in partial fulfillment of the requirements for the award of degree of

Master of Engineering

in

Software Engineering

Submitted By

Madhur Jain

Roll No. 801331012

Under the supervision of:

Dr. Ashutosh Mishra

Assistant Professor

CSE Department

COMPUTER SCIENCE AND ENGINEERING DEPARTMENT

THAPAR UNIVERSITY

PATIALA – 147004

July 2015

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "*Age-Group Prediction of Facial Images using different Classifiers*", in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Software Engineering* submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Ashutosh Mishra* and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

Madhur

(Madhur Jain)

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

(Dr. Ashutosh Mishra)

Assistant Professor, CSE Department

Countersigned by

(Dr. Deepak Garg)

Head

Computer Science and Engineering Department

Thapar University

Patiala

(Dr. S. S. Bhatia)

Dean (Academic Affairs)

Thapar University

Patiala

Acknowledgement

First of all I would like to thank the Almighty, who has always guided me to work on the right path of the life.

This work would not have been possible without the encouragement and able guidance of my supervisor **Dr. Ashutosh Mishra**. I thank my supervisor for their time, patience, discussions and valuable comments. Their enthusiasm and optimism made this experience both rewarding and enjoyable.

I am equally grateful to **Dr. Deepak Garg**, Associate Professor and Head, Computer Science & Engineering Department, a nice person, an excellent teacher and a well–credited researcher, who always encouraged me to keep going with work and always advised me with his invaluable suggestions.

I will be failing in my duty if I don't express my gratitude to **Dr. S.S. Bhatia,** Senior Professor and Dean of Academic Affairs, Thapar University, for making provisions of infrastructure such as library facilities, computer labs equipped with net facilities, immensely useful for the learners to equip themselves with the latest in the field.

I am also thankful to the entire faculty and staff members of Computer Science and Engineering Department for their direct-indirect help, cooperation, love and affection, which made my stay at Thapar University memorable.

Last but not least, I would like to thank my family whom I dearly miss and without whose blessings none of this would have been possible. To my parents, I own thanks for their wonderful love and encouragement. I would also like to thank my brother, since he insisted that I should do so. I would also like to thank my close friends for their constant support.

Date: July, 2015

Place: Thapar University, Patiala

Madhur

(Madhur Jain)

Abstract

A human face provides a lot of information which allows another person to identify their characteristics such as age, gender, etc. So the challenge is to develop an age-group prediction system by using the machine learning method. The task of estimating the human's age-group from their frontal facial images is very captivating, but also the challenging one due to the personalized and non-linear pattern of ageing which differs from one person to another. This work examines the problem of predicting the age-group of human on the basis of presenting a facial image with the improved accuracy of estimation. The aim of this study is to build up a framework and subsequently an algorithm that helps in estimating the age-group with the reasonable accuracy of the facial images.

In this work, a method is presented for the age-group prediction in which age-group is predicted by detecting the face or face landmarks using the Viola-Jones algorithm. After detecting the face, features including geometric features, wrinkles features are extracted and then these extracted features are used to train a classifier using Support Vector Machine (SVM) or K-Nearest Neighbors (K-NN). Finally, SVM or K-NN is used to categorize the age into one of the three different groups such as child, adult and old for the test data. The system used self-build database for the age-group classification. Finally, identification rate achieved using k-NN model produces better results than using SVM model as specified in experimental results.

Keywords — age-group prediction; Viola-Jones algorithm; Support Vector machine; K-Nearest Neighbors

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

The age group classification of human can be identified by facial features like identity, gender, age, nose, eyes, wrinkles, etc. that have engaged much attention in the last several years since face image processing techniques yield comprehensive application in various computer vision and graphics fields. The human age classification provides a vital role in the area of research based on vision application such as Human Computer Interaction (HCI), 2D and 3D recognition of face and virtual reality [1]. A lot of methods have been presented for the person's age estimation and mainly focuses on the analysis of human facial image and these are categorized as – Anthropometric Models, Analysis of aging manifold and regression. Anthropometric finds the intensity of wrinkles to classify into different age groups and other methods like aging pattern subspaces; regression has obtained the attraction latterly and provided decent performances.

Age-Group prediction can be regarded as the problem of pattern recognition implicating two common steps: extraction of features and identification [2]. From an extracted feature, identification can easily be done using regression and classification process. Age classification is basically perturbed with the training set through which system is trained and test set on which testing is applied for age classification. The main objective is to develop an algorithm that identifies the person's age from the extracted features. The system can be useful for preventing the young children from, not to have access the adult contents or materials from the internet and stop or prevent underage drinkers from buying alcohol, cigarette, etc. It provides a wide variety of applications like content analysis of multimedia, designing an interactive and intelligent robot. To attain our goal, good databases are needed like Morph or FG- Net database so that these databases can be used to train the classifier by using SVM or K-NN and employ the test set on SVM or K-NN classifier to resolve our problem. The main objective is age prediction so the work worries about the frontal images of the faces. Now firstly let's discuss some of the approaches like image processing, Viola-Jones algorithm, Support Vector Machine, K-Nearest Neighbors that have been employed in our proposed system implementation.

1.1. Image Types

There are 3 types of images which are defined below [3]:

- **Binary Image:** A logical array of 0s and 1s is referred as a binary image. Pixels are appearing as black with the value 0 and pixels are appearing as white with the value 1 as shown in Figure 1.1.
- **Grayscale Image:** It is also called as gray level, intensity or grayscale image. Grayscale images are the images that can be represented as a 2-D matrix. It becomes easier to work with the grayscale images in analyzing and performing mathematical operations and pixel-level transformation on an image. Intensity values are specified by the pixel values of uint8, unit16, int16 class array and single or double arrays. The value varies from [0, 1] for the single and double arrays, [0, 255] for uint8, [0, 65535] for uint16 and [-32768, 32768] for int16 class. Figure 1.2 shows the grayscale image example.
- **True Color Image:** In this image, three values specify each pixel, i.e. red, blue and green as shown in Figure 1.2. Intensity values are specified by the pixel values of uint8, unit16, int16 class array and single or double arrays. The value varies from [0, 1] for the single and double arrays, [0, 255] for uint8, [0, 65535] for uint16 and [-32768, 32768] for int16 class. True color image is also named RGB image.

1	1	1	1	1	1	1	1	1	1
1	0	0	0	1	1	0	0	0	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	0	0	0	0	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	1	0	1	1	1	1	0	1	1
1	0	0	0	1	1	0	0	0	1
1	1	1	1	1	1	1	1	1	1

Figure 1.1: Binary Image

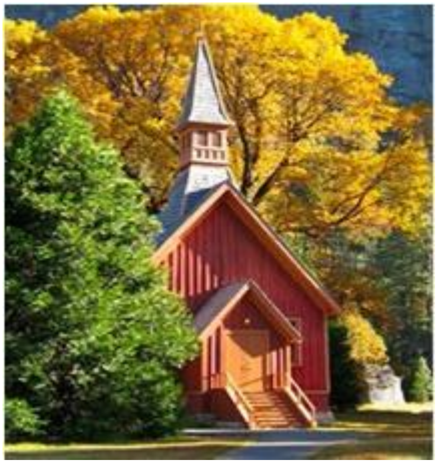


Figure 1.2: True Color Image [3]

Figure 1.3: Grayscale Image [3]

1.2. Digital Image Processing

A 2-variable function *f(x, y)* can be described as an image in which *x* and *y* are the plane coordinates, and *f* is a value which can be defined as gray level or intensity at any point *(x, y)* in the image. An image can be named as a digital image, if the values of *x*, *y* and *f* are discrete and finite. If the digital computer is used to process the digital images, then it is called as *Digital image processing*. There are some elements exist in the digital image with their corresponding value and location. These elements are called pixels [4]. Figure 1.4 shows the acquisition process of a digital image.

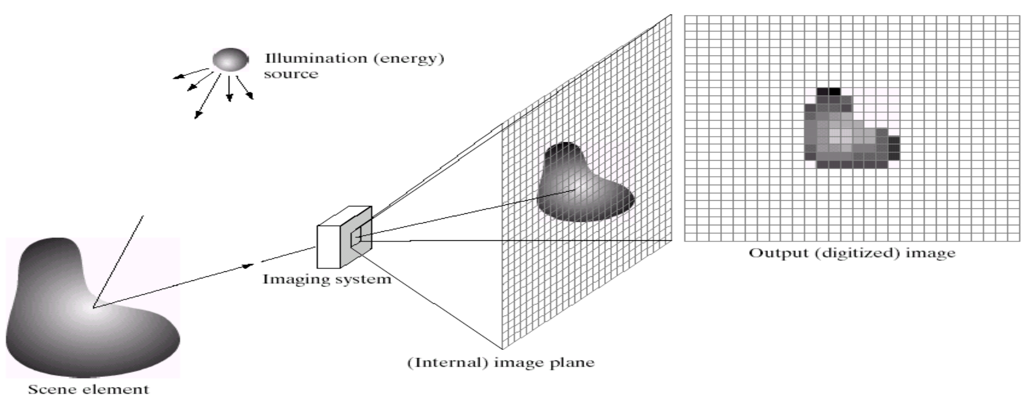


Figure 1.4: Digital Image Acquisition process [4]

In the above process, different approaches can be applied, but the aim is to use the sensed data for getting a digital image. Most of the sensors generate the output in a form of continuous voltage waveform. There are two processes, i.e. Sampling and Quantization are used in order to obtain a digital image from sensed data. Sampling is a process of digitizing the x, y plane coordinates and Quantization is a process of digitizing the amplitude f. Both the coordinates x, y and amplitude f are in the continuous form when the image is captured. To generate a digital image, a function has been pertained on the amplitude, f and also on plane coordinates x, y.

The work has employed *Viola-Jones object detection framework* for detecting the faces as it is considered as the fastest and the most referred and most precise pattern recognition technique for face detection. The main features which make it superior detection algorithm are:

- Robust – Always have high true positive rate (high detection rate) and fewer false-positive rates.
- Real-time – For the practical application, this algorithm takes a very less time i.e. about 1-2 frames per second for processing.

1.3. Viola-Jones algorithm

Viola-Jones algorithm consists of mainly four stages [5]:

- Haar-like features
- Integral image creation
- Adaptive-Boosting Training method
- Cascades of Classifiers

The features used by this method involve the addition of image pixels within areas of the rectangular region. In general, Viola and Jones use features that rely on the several different regions of rectangle area are more complex.

1.3.1 Haar-Like Features

These features are introduced by Viola and Jones detection framework due to their feature extraction computational simplicity. The value of each feature is the addition of the pixels in the rectangle with clear regions subtracted from the addition of the pixels in the rectangle with shaded regions. Viola-Jones algorithm that adapted the use of Haar-like features which can be evaluated at the constant time by using an integral image and uses four types of features illustrates in the Figure 1.5 below. The Haar-like feature extraction process on a facial image is displayed in Figure 1.6.

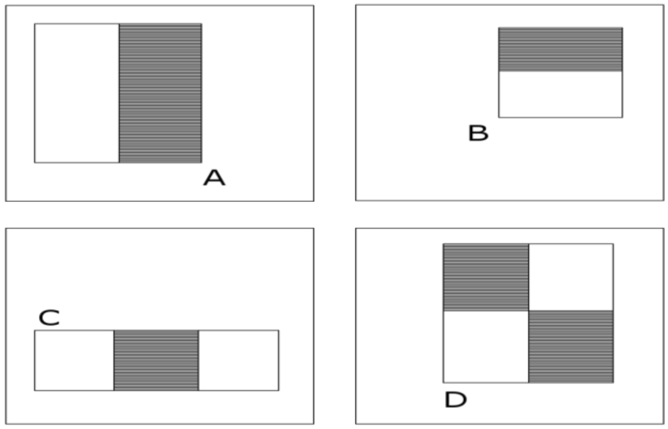


Figure 1.5: Types of Features used by Viola and Jones [5]

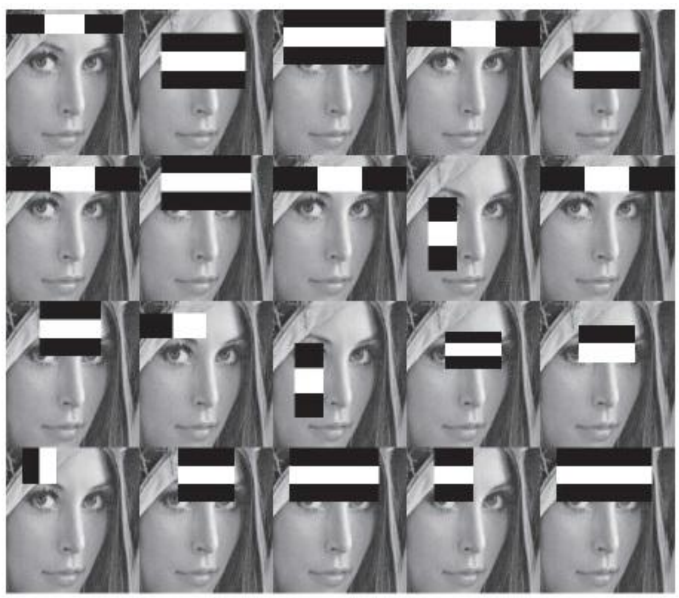


Figure 1.6: Haar-like features extracted from divergent scale

1.3.2 Integral Image Creation

Integral Image is a function which pre-processes the image by dividing the value of each pixel using normalization. The value of an integral image at (x, y) is the summation of pixels above and the left of (x, y) along all the boundaries of an image and can be computed in a single pass throughout the image (refer Equation 1.1).

$$ii(x, y) = \sum_{x' \le x, y' \le y} i(x', y') \tag{1.1}$$

Where '$ii(x', y')$' is an integral image and '$i(x, y)$' is an original image.

1.3.3 Adaptive Boosting Training Method

The adaptive boosting method is done for improving the efficiency of any learning algorithm is also known as *AdaBoost.* By setting levels of threshold, this method is used to identify the existence of Haar-like feature. The value of each feature is the summation of the pixels in the rectangle with clear regions subtracted from the summation of the pixels in the rectangle with shaded regions. If the difference is above the value threshold, that feature is present otherwise not present.

Secondly, within any sub-window of an image, there exist a large number of Haar-like features. So, the process excludes the complementary features and concerns only about critical features. To attain this goal, the weak learning algorithm presented by Viola Jones chooses only a single feature of the rectangle which best split the positive samples from the negative samples. For each feature, threshold classification function is determined by the weak learner. A set of weak classifier are then combined to generate one strong classifier.

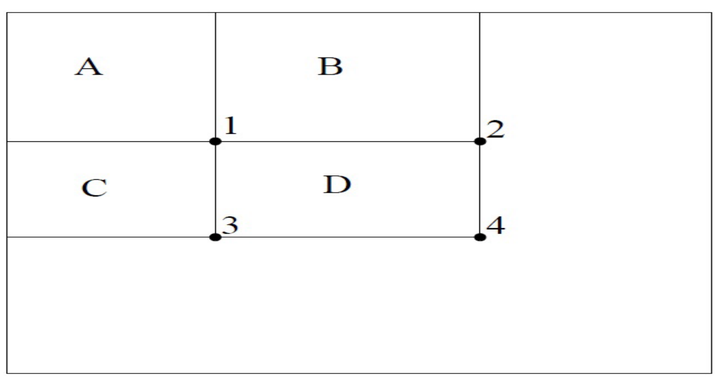


Figure 1.7: Pixels Sum within rectangle [5]

In the above Figure 1.7, the integral image value at place 1 is the addition of pixels in region A. The value at place 2 is A + B, at place 3 is A + B + C, and at place 4 is A + B + C + D. The sum within D can be calculated as 4 + 1 – (2 + 3).

1.3.4 Cascades of Classifiers

Viola Jones described an algorithm for constructing cascaded classifiers that can be used for increasing the rate of detection with lower computation time. This method is to detect all positive sub-windows while rejecting the negative sub-windows. It may consist of many stages where each stage is required for more than 50% of negative instances elimination as long as positive rate reaches to 100%. The cascaded structure is depicted below in Figure 1.8.

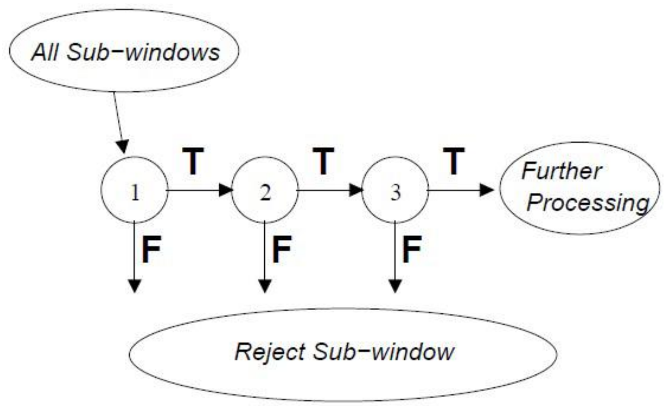


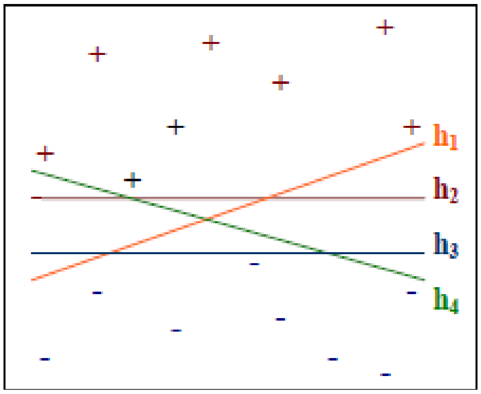
Figure 1.8: Cascade Structure

1.4. Support Vector Machine (SVM)

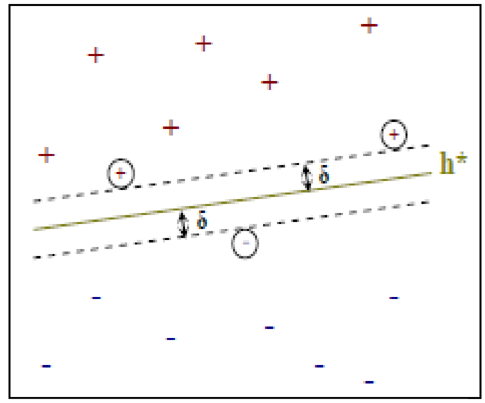
Support Vector Machine is a supervised learning method that has recently achieved a lot of popularity in the area of visual pattern recognition. SVM has also been successfully pertained to a large number of applications such as text recognition, bioinformatics, particle identification, database marketing etc.

1.4.1. Optimal Hyperplanes

The main aim is to discover an optimal hyperplanes that maximize the margin between one or more classes. Let us assume that the data is collinearly separable. Figure 1.9 shows the optimal separable hyperplane where Figure 1.9 (a) displays the various hyperplanes that separate the training data. SVMs pick hyperplane h* in Figure 2 (b) that best separates the data with the δ margin.



1.9(a) Separating hyperplanes h_1, h_2,



1.9(b) Optimal separating hyperplane, h* with the margin

Figure 1.9: Optimal Separable Hyperplane

Function complexity reduces with the increasing margin of separation δ. So by maximizing the δ explicitly, generalization error is minimized and thereby results better generalization. Margin size is not dependent on the data dimension; hence the problems due to the over-fitting of high dimensional data are reduced greatly. The no of training vectors lay on the margin are conserved, well-known as Support Vectors that carry the details about classification problem. In the Figure 1.9, three circled trainings are preserved as Support vectors.

1.4.2. Support Vector Regression (ϵ-SVR)

The Support Vector Regression (SVR) was introduced by V. Vapnik et al. [6]. Age estimation involves classification of an unseen image into one of predefined groups. However, age is a number. The goal is to study the relationship between the coded depiction of the image and number that signifies the age. So, the system uses Support Vector Regression Machines. SVR employs the ϵ-insensitive function as shown in Figure 1.10. If the variation between the actual value and the calculated value is less than ϵ[23], and then there is no error in function. The point surrounded by the dotted region deviates by ζ and is treated as an error of training and is castigated by SVR in a linear fashion.

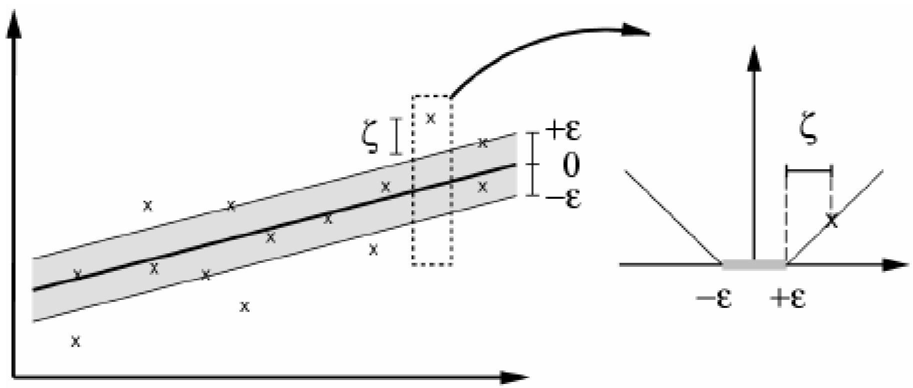


Figure 1.10: ϵ-Insensitive Zone in SVR

1.4.3. Multiclass Classification

The main aim of building an SVM (multisvm) is to divide the classes into two or more categories and is resolved by dividing it into the multiple binary problems. There are two general methods for constructing such a classifier:

1. The *one-versus-all* method: This method is basically used to train one classifier for each l_i label that separates between the label l_i and the other classes. A new model with the highest output of the classifier is assigned to the label.
2. The *one-versus-one* method: this method is used to train one classifier for each label pair and sample with highest votes is assigned to the label.

Benefits of SVM

SVM provides several different features for the aging function learning. Unlike all other classifiers and learners such as decision trees, neural network etc, SVM is interdependent on the input data dimension. In general, images contained in the training data have high input data dimensionality and commonly require more images to train the classifier. So, SVM is better selection for classifying the age groups with the limited training data. Also, non-linear functions can be produced on the basis of kernels parameters selected which are used to determine a function that shows input data set.

For these reasons, and success of using SVM in several different age classifications or face identification methods, SVM has been chosen to train the aging function.

1.5. K-Nearest Neighbors (K-NN)

In the pattern recognition, k-NN is one of the methods that is used for the classification problem and the regression problem. In both methods, the feature space consists of k training samples as an input. The output of the k-NN basically rely on the method used i.e. classification or regression.

- In classification, majority vote classifies the object of its neighbors where the object is being allocated to the class among its k-NN (in general, k is user defined small constant and a positive integer).
- In regression, output is the object value which is the average of its k-NN values.

The training part of the algorithm contains the feature vector space and training sample class labels. The idea behind the k-NN is to identify the k number of samples in the training set and then utilize these samples to classify the test samples into a class. Whenever the neighbor is exploited, it implies that there is some parametric distance that is to be computed between samples on the basis of independent variables. It will worry only about the popular distance measure, i.e. Euclidean distance and is defined between the points (x, u) below in equation 1.2.

$$d(\mathbf{x}, \mathbf{u}) = \sqrt{\sum_{i=1}^{n} (x_i - u_i)^2} \tag{1.2}$$

It is a noteworthy fact that the thought of using k-NN to classify the age group can be very effective when a large number of training samples in our database is taken and that would help in reducing the misclassification error.

1.5.1. Shortcomings of K-NN

One of the most decisive shortcomings of k-NN is the time required for finding the nearest neighbor in the huge training set can be more prohibitive but this can be overcome by removing the redundant points in the training sample and working on reducing the dimensions using various techniques such as Principal Component Analysis (PCA), Canonical Correlation Analysis (CCA), or Linear Discriminant Analysis (LDA).

1.6. Structure of the Thesis

The next chapter, i.e. chapter 2 describes the literature survey based on different approaches for the age prediction. Chapter 3 describes the problem statement. Chapter 4 explains the step-by-step proposed work implementation details of age classification, including image preprocessing, feature extraction process and classification (via SVM or K-NN). Chapter 5 shows the experimental results achieved from the implementation and finally, chapter 6 provides conclusion based on experimental results and suggests some possible future directions for the work.

Chapter 2
Literature Review

There are many different age group estimation approaches have been proposed in the past. The major steps that have been used in the age group classification are mostly same such as image preprocessing, feature extraction, training and testing. So, some of the methods or algorithms have been defined proposed by the authors.

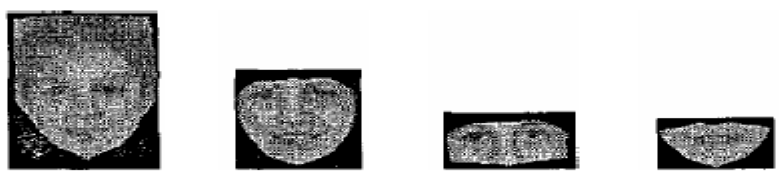
2.1. Geometric Features and Wrinkles Feature based Approaches

The age determination algorithm was first proposed by Lobo and Kwon [7]. They used geometric ratios to make a distinction between babies and other groups and classified the age into three categories: babies, adult and old. Their method is based on the analysis of skin wrinkles and geometric ratios where the geometric ratio is evaluated first from the facial wrinkles features to differentiate babies from adults. The ratio of the gap between the eyes to the gap between the eyes and nose is used to differentiate child from adults. After distinguishing the babies, skin wrinkles features is measured to differentiate young from adults and then combine geometric ratios and skin wrinkles features to find the age group. But the performance rate to identify children was below 68% and there were several issues found in their method such as testing was done only on about 47 images and high resolution images are required for the prediction of results.

Horng et al. in [8], realized the limitations of Kwon and Lobo and proposed a model that includes the different approaches to solving the wrinkles features and geometric ratios. They have used neural network to do classification and attained the accuracy of 81.6% for 230 test images.

Hayashi et al. in [9], proposed a method that focused on the facial wrinkles for age and gender prediction. They took 300 images ranging from 14 years to 65 years of age under organized conditions. Skin section is extracted from the facial images and then histogram equalization is done to enhance the wrinkles features and then shorter and the longer wrinkles are extracted using DTHT (Digital Template Hough Transform). Finally, age and gender are predicted by using a look-up table. Their experiment was not successful enough as they have achieved 27% of accuracy on the age prediction and 83% on gender estimation and the point which is taken into consideration that the size of their test dataset has not been defined for their results. They have faced some difficulties in extracting the wrinkles on female's age between 20 and 35 due to the makeup presence.

Lanitis et al. in [10], focused on the different facial parts for the age estimation. He presented an algorithm that was based on the statistical face models. His work involved the following face parts: whole face (including hair), internal face (excluding hair), lower part of face, upper part of the face. Figure 2.1 displays the used regions of the face. Experimental results showed that the region around the eyes is most crucial for age prediction and error has been minimized by the upper facial part. He asserted that hair (when whole face is used) produces the negative impact on the results. His work was limited to only 0 to 35 years of age, so he did not use the faces with more wrinkles and included 330 images of which only 80 images were utilized for testing purpose.



(a) Whole face (b) internal face (c) eye region (d) mouth region

Figure 2.1: Different Facial Regions [10]

2.2. SVM based Approaches

Chen, Yi-Wen, et al. in [11], proposed method based on the Lucas-Kanade image alignment method and SVM. Firstly, the morphology procedure was used to reduce the noise in an image and then human face landmarks are obtained by applying the color region mapping and finally, cascade method is employed to establish whether candidate face is a human face or not. After the detecting the face, an image enhancing process was used, including face normalization to 120x100 grayscale image and face illumination that is remunerated into 128 value image based on equation (2.1) and (2.2) for improving the efficiency of feature extraction.

$$I_{ave} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{I}_i \qquad (2.1)$$

$$I'_i = (128 - I_{ave}) + I_i \tag{2.2}$$

Where N is a number of pixels, I_i is an i_{th} image intensity and I_{ave} is the average value of intensity. I'_i is the normalized value of intensity.

They took up a Lucas-Kanade image alignment method to locate the 52 features points and used them to construct an active appearance model (AAM). Then, the warped images have been into the two divisions, one for the training set and another for the test set. Texture features are then sent to the SVM after facial image warping to predict the level the level of each group. Finally, average recognition of 81.1% has been achieved using gray scale value and but when applied Sobel detection method, they got 87.8% of recognition rate and achieved 82.2% of recognition rate after combining the gray image with the edge image.

Tonchev, K., et al. in [12], presented a system based on a combination of subspace projection algorithm and vector classifier for the age group estimation and in addition, face detection algorithm is integrated to guarantee the detection of faces. Their system consists of Face Detection, Normalization of face, Subspace Projection, Support Vector Machine for the classification of age as shown in Figure 2.2. Face detection includes both Haar-like features and the Convolution Neural Network (CNN) where CNN role is to reduce the inferring rate. After detection of face, face normalization is done on that face to perform the lightning normalization and geometric alignment. The geometric alignment guarantees low dependence on the face rotation, while normalization ensures the better lighting conditions. In the next phase, a subspace projection is carried out for noise reduction by a combination of algorithms Spectral Regression and Principal Component Analysis. Finally, SVM classifier is applied to age group prediction.

Figure 2.2: Age Group Classification System [12]

Khryashchev et al. in [13], developed a novel algorithm including adaptive extraction of features using local binary pattern and SVM classification. They have presented experimental results on MORPH, FG-NET and their own database and predict the comparison of humans and machines. Firstly, the image is preprocessed by using a color space transformation process and scaling process. Additionally histogram equalization is performed due to the unsteady lightening and it has also been used to improve the image contrast. After the image enhancing process, features are extracted using the local binary pattern of all images and then features were then passed to the SVM to train the classifier. Some performance standard metrics was calculated to test the algorithms:

- Mean Absolute Error (MAE) - Absolute mean difference between real aged and predicted ages.
- Cumulative Score (CS) – the probability such that age falls within the interval from the real image.
- Probability Density function (PDF) – to find the age prediction error.

It has been predicted that total MAE score on real life dataset using LBP-SVM algorithm is 6.94, 7.29 for MORPH database, and 7.47 for FG-NET database. The value 4.2 of MAE indicates that algorithm still requires some improvement to show the human comparable results.

Weixing, et al. in [14], proposed a method that extracted features by three methods. Firstly, texture features, i.e. uniform local binary pattern (ULBP) is extracted using Gabor wavelet transform. . Figure 2.3 shows the formation process of the Gabor_ULBP age feature. Secondly, facial partition based on the ASM approach by which ULBP histogram and complete partitions of the face is extracted. Figure 2.4 shows the formation process of the ASM_ULBP age feature. Thirdly, ratio feature based on facial skin areas and wrinkles region is extracted. Figure 2.5 shows facial skin areas and edge wrinkle detection. They have used FG-NET database and self made face database for the training and testing. Adaboost based binocular location method is used to label the eye position. Finally, strong SVM classifier is employed according to three extracted features above and their method reached a recognition rate of 85.75% with the 180 × 180 resolution images.

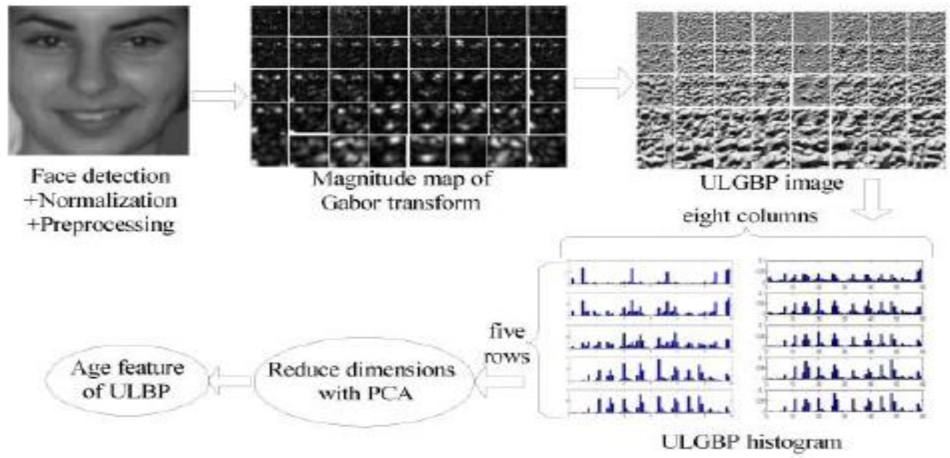


Figure 2.3: Formation Process of Gabor_ULBP Age Feature [14]

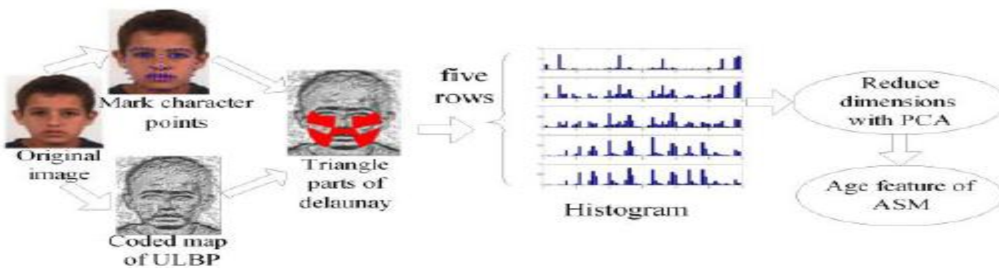


Figure 2.4: Formation Process of ASM_ULBP Age Feature [14]

Figure 2.5: Facial Skin Areas and Edge Wrinkle Detection [14]

Guo, Guodong, et al. in [15], developed a Probabilistic Fusion Approach (PFA) that produce higher age estimation performance and fuses regression and classification process as display in Figure 2.6. They have chosen SVM classifier and Support Vector Regression (SVR) for regression. Both SVM and SVR work sequentially. Initially, regression method was used to get the intermediate decision and then intermediate results were then sent to the SVM classifier for the multi-class classification of age.

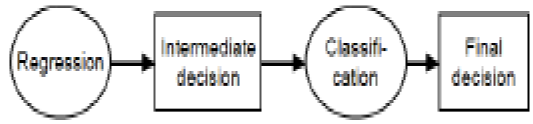


Figure 2.6: The PFA approach

2.3. K-NN and NN based Approaches

Gunay *et al.* in [16], exercised Local Binary Pattern (LBP) for the feature extraction and split the image into n regions from which LBP histograms is produced for each image and concatenate all histograms into a feature vector. Face is detected using Neural Network initially and calculated the vertical and horizontal projections of grayscale image to locate positions of the eyes and eye pupil and then histogram equalization is applied to improve image contrast occurred due to the unsteady lightening. LBP histograms produced for each image have used to classify the image into one of the predefined classes of age. They used K-Nearest Neighbors (KNN) to make a decision of the age class of an image and provided the accuracy of 80%.

Mohammad Ali et al. in the paper [17] proposed age-group estimation algorithm on the basis of Histogram of Oriented Gradients (HOG) features. Initially, an image is preprocessed by cropping the image to locate the eyes on which the HOG feature extraction algorithm is applied. This algorithm provides the histogram of oriented gradients in the local parts of image and features is computed from the several different regions such as eye-corners, forehead, near cheekbones and below the eyes. For each image, these features are concatenated to make a feature vector and then probabilistic neural network (PNN) classifier is used to classify the every image in one of the age groups by using feature vector. Figure 2.7 shows the flow of method.

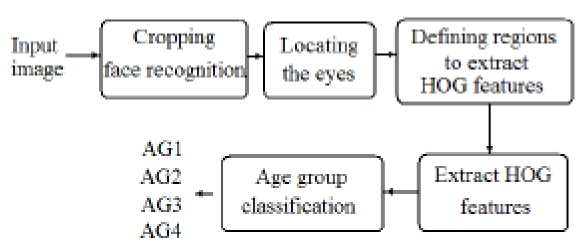


Figure 2.7: System block diagram based on HOG Features [17]

Izadpanahi *et al.* in [18], proposed a method that involves geometric analysis of feature and classifying the age group using three classifiers SVM classifier, neural network classifier (NN) and density based linear classifier (LDC). Geometric feature initially finds facial landmarks and then calculates the six biometric ratios by using seventeen landmarks and ten facial measurements as shown in Figure 2.8. After extracting the biometric ratios, these ratios are used by the classifiers to categorize the images into five different age groups, namely AG1 (0-2), AG2 (3-7), AG3 (8-19), AG4 (20-39), AG5 (40-60). The method has achieved a success rate of 98% in classifying the babies (0-2) from other age groups.

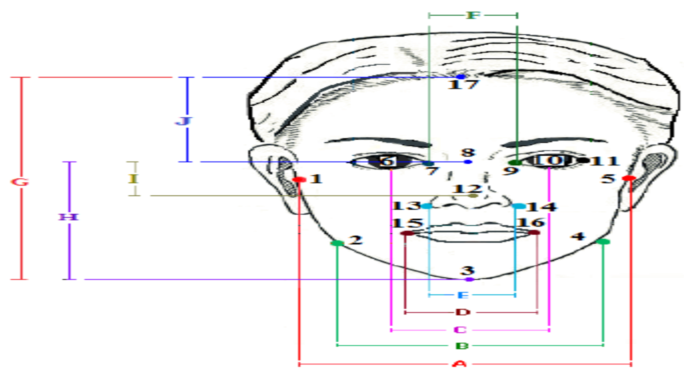


Figure 2.8: Ten Facial Measurements with Seventeen Landmarks [18]

Ren C. in [19], presented a method that involves two stages: one was the image preprocessing and enhancement stage and another is face detection with the Adaboost algorithm using Haar-like features. They have simulated their results on the FG-NET and MORPH database. Images are firstly preprocessed i.e. images are converted into grayscale images. Viola Jones method that adapted the use of Haar-like features is used to detect the face and eye by cascading a weak classifier. Within the sub-window of an image, there exist a large number of Haar-like features. So, process excludes the complementary features and concerned only about the critical features. To achieve this goal, they applied weak learning algorithm proposed by Viola and Jones that chooses a single feature of the rectangle which splits the positive samples from the negative samples. After image preprocessing and feature extraction, classifier got trained by using the SVM based on features and then SVM categorized the images in one of the age groups and achieved the success rate of 76% in set1 and 93% in set 2. So the average recognition rate achieved was 84.5%. The subjective questionnaires are also designed and showed that people are not proficient of recognizing the human's age group accurately.

Weixin Li et al. proposed a novel algorithm based on Sparse Representation based Classification (SRC) in [20] which chooses human age in a hierarchical manner. They used a FG - NET database for their experiment. Initially, the image is preprocessed by normalizing the image. After image normalizing, Local Binary Patterns (LBP) method is used to extract the human facial texture features and then the shape features were extracted by using the Active Shape Model (ASM). They estimated the age on the basis of two human life stages: the phase from birth to adult and the phase from adult to old age. Since, shape of face changes drastically due to the movements of bones during the 1^{st} stage and vaguely during the 2^{nd} stage. So the facial features are radically differing between these two stages. Therefore, in the first step, quadratic function was used to classify the images into one of the stages and in the latter step, further preprocessing of the image was done to solve the age estimation by employing Sparse Representation based Classification (SRC). Since SRC required a lot of training samples of each class which made the efficiency of age classification limited. So, Ordinal Hyper-planes Ranker (OHR) was used to improve the results of age estimation. They evaluated the performance of their system by using two parameters: Mean Absolute Error (MAE), which is the mean value difference between the real age and estimated age and Cumulative Score (CS) which is the absolute error between the actual age and inferred age.

Thukral et al. in [21], implemented the hierarchical approach where the images of face was divided into several age groups and separate regression model was being learned for each age group. They exploited FG-NET database as their training and test set. Many methods have been used by them such as geometric features for extracting the features and Relevance Vector machine (RVM) method as a regression technique. The main purpose of the RVM is to learn the functional relation between the two variables. During this phase, some training samples are allowed to overlap so that model can classify the errors that may occur while allotting the image to one of the age group. Finally, they classified the test set using five different classifiers such as Nearest Neighbor, μ-SVC, Partial least squares (PLS) and they used the majority rule for the classification of test images into the appropriate age group.

Nithyashri J. et al. in [22], delivered a method in which Wavelet Transformation (WT) technique for the extraction of features and Adaptive Resonance Theory Network (ART) method as an artificial neural network for the classification of age were used. The FG-NET aging database was used to obtain the efficiency of their method. Primarily preprocessing was done by converting input facial color images into gray-scale images and then features were extracted using Wavelet Transformation which reduces bits required of the image. Two types of features have been extracted in their study includes Coif feature and two-level Haar features. The features like nose, eyes, chin, and mouth were extracted. After extracting the features, Euclidean distance was used to measure the different Feature Point Distances such as FPD_1 is the distance between the eyes, FPD_2 is the distance between the middle of eyes and nose, FPD_3 is evaluates as distance between the eyes and mouth, and FPD_4 is measured as a distance between the mediocre of eyes and chin. The distance between the (w, x) pixel and (y, z) pixel were measured by the formula show in 2.3. The Adaptive Resonance Theory Network was trained based on the feature point distance to classify the facial images into one of the age-groups- child, young, adult and senior adult.

$$D_E[(w,x),(y,z)] = [(w,y)^2 + (x,z)^2]^{\frac{1}{2}} \tag{2.3}$$

Yang, Xi, et al. in [23], modeled the problem of age estimation based on the framework of Multiple Instance Learning (MIL) and proposed an algorithm called Witness based Multiple Instance Regression (WMIR). The main idea behind multiple instance regression algorithms (WMIR) is to find the both positive instances and the negative instances and use both these instances to train the classifier. Firstly, the image is preprocessed for the noise reduction using Principal Component Analysis (PCA). The probabilistic weighted Support Vector Regression (pw-SVR) technique was designed for the estimation of age. Logistic discriminant metric learning (LDML) was used for the features space and pw-SVM was trained using these feature space. At last, pw-SVM categorizes the age accordingly.

2.4. Active Appearance based Approaches

Liu, Li in [24], presented an approach in which age was categorized into five different age-groups. Initially, all the images were converted into grayscale and then preprocessed using the image intensity normalization implemented by histogram equalization. The Active Appearance Model has been utilized for extracting the features so that these features could be used to train the classifier with the Gaussian Radian Basis Function kernel (RBF). Since, feature space was so large, so they used Principle Component Analysis (PCA) to reduce the length of feature space. In the last step, test set was sent to the Support Vector Machine classifier to categorize the age into one of the five groups based on the training dataset.

Lee, Seung Ho et al. in [25], classified the age the based on local age group modeling, which is erected by clustering trained faces. This method also helped in dealing with large variations of facial appearance. Whole training images of an age group were decomposed into a different set of face clusters that avoided the degradation of classification due to some disagreeable faces. They provided the effective way of computing the distance between the centroid of face cluster and the test face and way of computing distance between training face sample distribution formed and the test face. These measures were used to improve the distinction between the clusters of different age groups. The block diagram of the proposed method is displayed in Figure 2.9. Since the face clusters may differ with the different database, hierarchical method of clustering seems more suitable than the k-means clustering. They used LBP histogram features were extracted from them and then classify the age group based on hierarchical clustering and the achieved estimation rate about 60%.

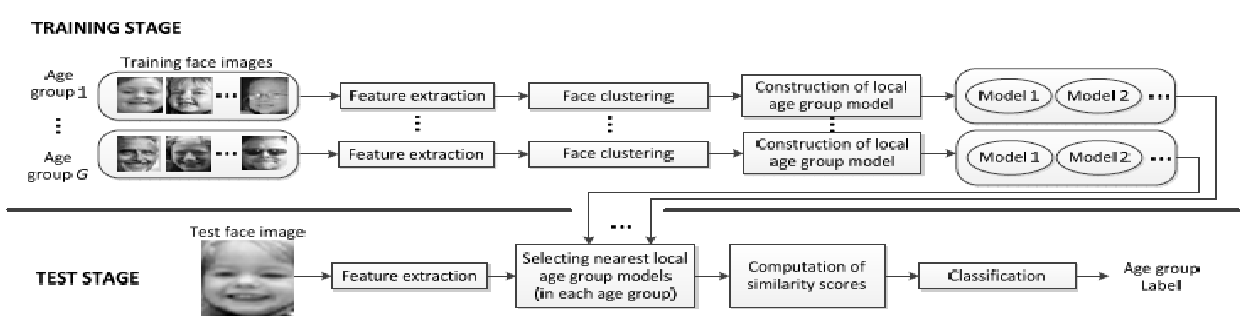


Figure 2.9: Age Classification on the basis of Local Age Group Modeling [25]

Ueki, Kazuya et al. in [26], presented a framework for the age-group classification under different lighting conditions. Their method as based on the combination of two-phased approaches named 2DLDA and LDA and their results of the experiment showed that their approach improved the accuracy of classification more than the LDA approach and PCA-based approach. PCA is an approach which calculates a vector that has the biggest variable in the training data and LDA is a method that discovers a projection for maximizing the ratio between the class scatter and within the class and features can also be extracted using LDA. Sometimes Small Sample Size Problem (S3 problem) may be encountered due to the high dimensionality of facial images. To overcome, PCA was used for the reduction of dimensionality. The Gaussian model classifier was trained using a training-set images based on LDA and used to classify the age-groups for the test set. They used a WIT database for the various lighting images and attained the accuracy rate of 46.3% for 5-year range, 76.8%for 10-year range and 78.1% for 15-year range age-group.

Chao et al. in [27], proposed an approach of age estimation with the three narrative contributions. Firstly, the relation between the age labels and facial features was discovered based on dimensionality reduction (reduce the feature size) and distance learning metric. Then to solve the disparity of age classes, the intrinsic ordinal relationship has been exploited among age based on label sensitive concept. At last, the local regression technique is exploited to confine the human ageing complex nature. They suggested a Label-sensitive Locality Preserving Projections (LsLPP) Label-sensitive Relevant Component Analysis (LsRCA) using AAM for the adjustment of distance metric. They used a FG - NET database to get experimental results. The Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) are combined to generate excellent results with Mean Absolute Error (MAE) of 4.38.

Most research in the area of age prediction is limited by the good choice of database used and the size of the database. Some researchers have only focused on the certain age groups, while some have employed the wide range of classification. Due to the lack of quality database, a universal age prediction function for the wide range of ages is yet to be developed. From the previous work, it can be concluded that the region around the eyes was most crucial for age prediction and hair produces the negative impact on the results. In this thesis work, main focus is on the geometric features and wrinkles features for the age classification. Viola-Jones algorithm has been used which adapted the use of Haar-like features for the detection of face landmarks such as face, nose, eyes etc. and used geometric features and wrinkles features for the feature extraction. Two different classifiers have been used such as SVM and k-NN to classify the age into three different groups such as child, young and old etc.

Chapter 3
Problem Statement

The problem of Age classification from the facial images is very captivating, but also the demanding one because age of human varies based on the various factors which may be internal factors or external factors. Internal factors vary age include gender, genetics etc. while the external factors that affect the age include lifestyle, drugs, ethnicity, etc. and these two factors could make it complicated to perfectly formulate the human growth pattern. The facial ageing estimation process that has been developed obtained a high accuracy rate for the baby faces than the adult faces, but for the adults this process has been a complicated task due to the occurrence of different patterns of ageing, internal factors, skin texture, and external factors for some years. It is also worth mentioning that age-group prediction has been useful in the different systems such as demographic classification, Age Specific Human Computer Interaction (ASHCI) and image datasets indexing etc.

In the automatic age classification, the main objective is to develop a sacred algorithm that enables to classify the age-group based on feature extracted facial images. One of the main challenges of the age classification is the accurateness level, which is due to the intricacy of the human ageing pattern. So, it is not only adequate to classify the human age, but also essential to predict it as precisely as possible. Another important issue that is relevant to the age prediction problem is the age-groups range and this parameter is a key aspect as different characteristics of ageing pattern appear in different age-groups, hence the system got trained to cope with specific ranges might not be relevant to a more diverse range of age-group. Therefore, in this study, we are encountering the human age-group prediction task between the young, adult, and old to an acceptable degree of classification accuracy based on facial images.

Chapter 4
Methodology

The purpose of this thesis is to classify the age into different age-groups such as child, adult and old. Age-group prediction can be regarded as a pattern recognition problem. Each age can be considered as a class; therefore age prediction can be viewed as a classification. Figure 4.1 shows the process of the age-group prediction system. Firstly, every image is passed to the system to preprocess the image so that they can be used in the database. After that frontal face landmarks are detected of every image like face, mouth, nose by using the Viola-Jones algorithm with help of OpenCV library and then extracted the feature points like Haar-like features, geometric features and wrinkle features. After extracting the features, training dataset is created by using them, which is then passed to the SVM or KNN classifier to train it. After that, test dataset is passed to the classifier which then classifies the images in one of the age-groups for the test data.

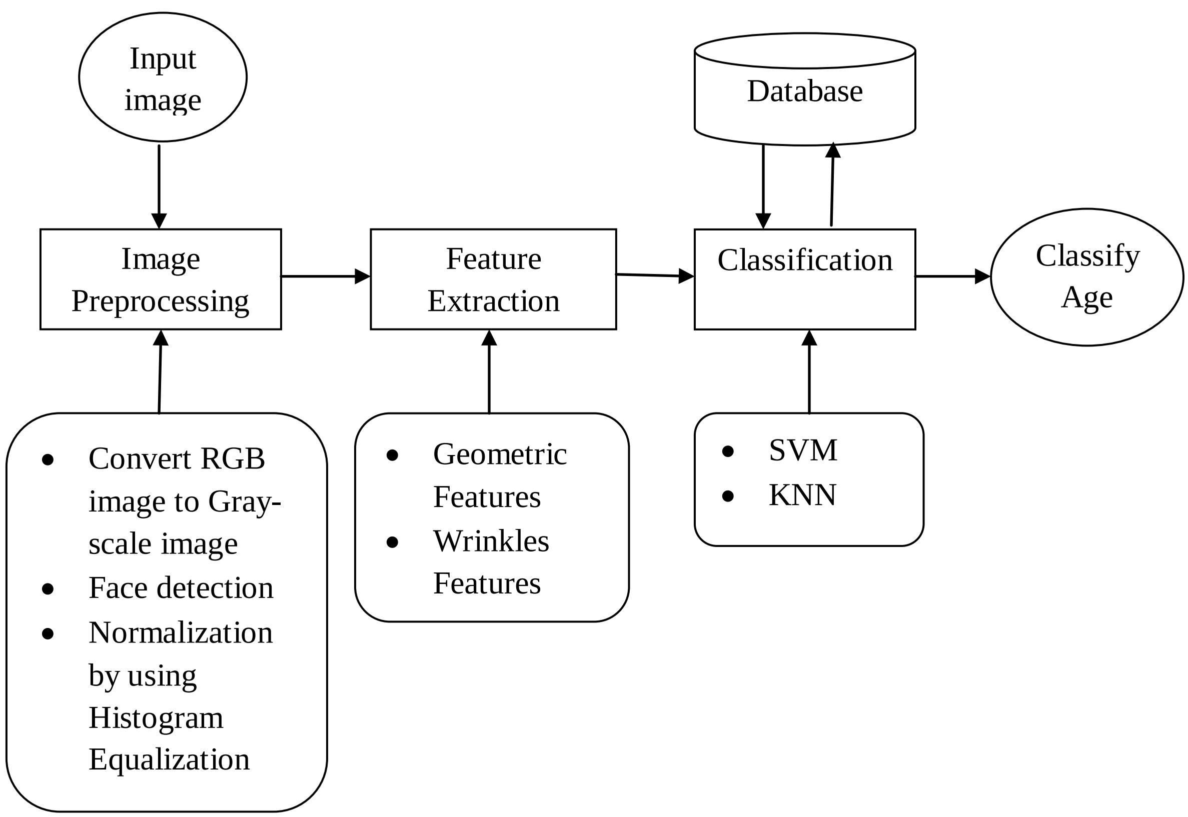


Figure 4.1: Age-Group Prediction System

4.1. Image Preprocessing

Image preprocessing is a very essential process in the image processing and it may have a significant impact on the image analysis result because in general, most of the images used in the database include some superfluous information, unsteady lightening in an image and sometimes the contrast of an image is also very poor which make it very intricate to process that image. The basic sequence of steps that have been involved in the image preprocessing is shown in Figure 4.2.

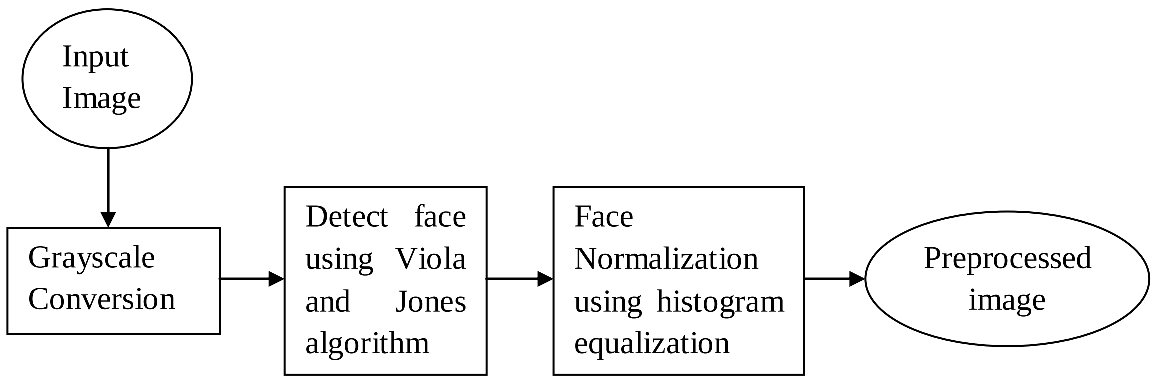


Figure 4.2: Image Preprocessing

4.1.1. Converting of RGB image into the Grayscale

Grayscale conversion is the first operation of image preprocessing that involves the conversion of color or RGB image to grayscale image using MATLAB function rgb2gray(). Although, color or RBG images are the one which could be visually alluring, but they hide the cogent low level image information which is not required in this work, so grayscale conversion is necessary. Grayscale images are the images that can be represented as a 2-D matrix. It becomes easier to work with the grayscale images in analyzing and performing mathematical operations and pixel-level transformation on an image. Moreover, features extraction method would perform proficiently with these images in acquiring the facial features. Grayscale conversion from color or RGB image is shown in Figure 4.3 where Figure 4.3 (a) shows the RGB image and Figure 4.3 (b) shows the corresponding grayscale image.

Figure 4.3 (a): RGB image Figure 4.3 (b): Grayscale image

Figure 4.3: Grayscale Conversion

4.1.2. Face Detection

The second step in the age prediction system is to detect the frontal face in an input image or video sequence. Identify the face within an image is termed as face localization or dace detection and locating the face across the various video sequence frames is termed as face tracking. The work has employed face localization or face detection process in our method based on the concept of Viola-Jones algorithm as described in the chapter 1. This face detection method adapted the use of Haar-like features. These features predetermine the existence of slanting contrasts between the regions in the image. Several different vigorous face detection algorithms have been described in the literature, but OpenCV face detection method is used in our work. In the OpenCV method, a classifier gets trained with the help of face images and non-face images where positive samples are the images with the face and negative samples are the images with non-face. After training, all the locations are being checked by the classifier to identify faces in an image. Figure 4.4 shows the detection of faces.

Figure 4.4(a) Original Image

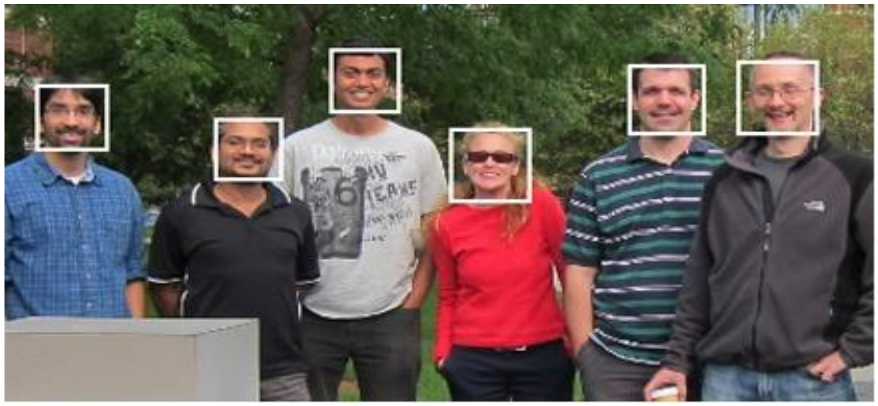


Figure 4.4(b) Detected Faces

4.1.2.1. Face Landmark Detection

In the landmark detection, eyes and nose are located on the face images using cascade classifiers similar to the detection of face as shown in a Figure 4.5. The cascade classifiers are already got trained in the OpenCV library. The rectangle coordinates of eyes and nose are sent to the module. The eye detection is basically used to rotate the image to balance both y-coordinates of eyes.

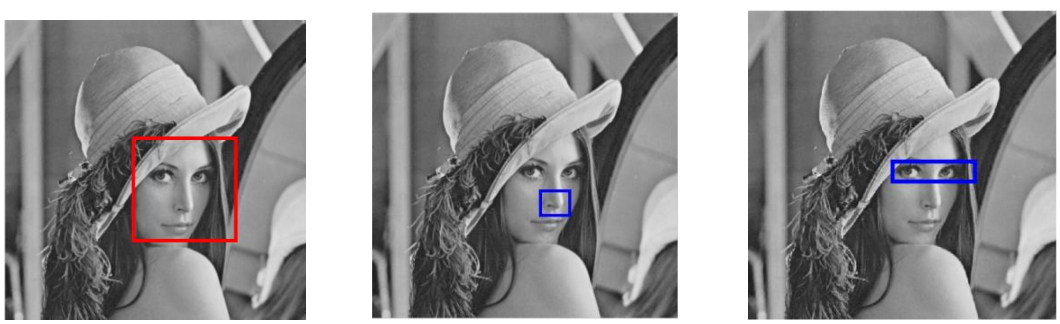


Figure 4.5: Face Detection Modules

4.1.3. Face Normalization

Since, most of the images are captured in the unrestrained illumined environment, so the illumined reimbursement is a crucial step which is done for the further preprocessing of an image. All the faces from the original picture are cropped and resized them into size of 80x80 pixels. After cropping, image normalization using histogram equalization method is performed on the images using MATLAB function ‘histeq’ due to the unsteady lightning. Image intensity values are spread by the histogram equalization over a large area and image contrast is also improved as shown in Figure 4.6. As a result, images are all set for the extraction of features. The intensity of the histogram equalized image is defined in equation 4.1.

$$S_k = \sum_{j=0}^{k} \frac{n_j}{k} \tag{4.1}$$

Where k = 0, 1, 2, 3, 4. . . . R-1 and S_k is the histogram equalized value in the range R for the kth intensity values in the original image and the target image. 'n' is the number of pixels and 'n_j' is the number of pixels in an original image having intensity value i.

Figure 4.6(a) Image before Histogram Equalization

Figure 4.6(b) Image after Histogram Equalization

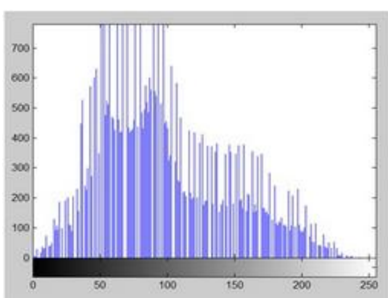


Figure 4.6(c) Histogram before Equalization

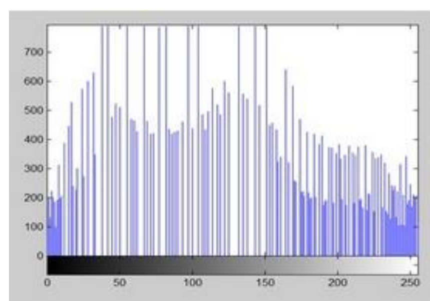


Figure 4.6(d) Histogram after Equalization

4.2. Feature Extraction

The range of the images experienced in this system exhibit substantial changes in the texture of face than changes in the facial shape. This is due to fact that adult ageing is exemplified by the texture of the skin in the form of creases and wrinkles, unlike the ageing of a child that is enormously characterized by the changes in facial shape. Thereupon, Geometric features and wrinkles features (detected by the canny edge detection algorithm) have been for the extraction of features. The method based on features uses all the information contained in an image and uses that information as a set of features for identifying the image, for example pixel-to-pixel position, edges, pixel distance, etc. In this work, five feature points have been utilized where four features are the geometric distance features and the fifth is a wrinkle feature.

- ***Geometric Features***

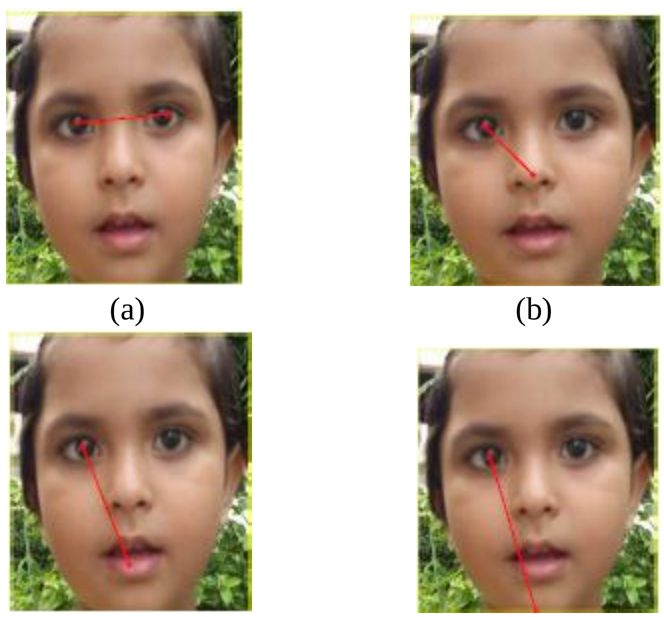
The geometric distance features includes the distance between the two eyes, the distance between eye and nose, distance from eye to lip, and distance from eye to chin is calculated as shown in Figure 4.7. Four features F1, F2, F3 and F4 using four distance values is calculated as follows:

F1 = (distance between left eyeball to right eyeball) / (distance from eyeball to nose)

F2 = (distance between left eyeball to right eyeball) / (distance from eyeball to lip)

F3 = (distance from eyeball to nose) / (distance from eyeball to chin)

F4 = (distance from eyeball to nose) / (distance from eyeball to lip)



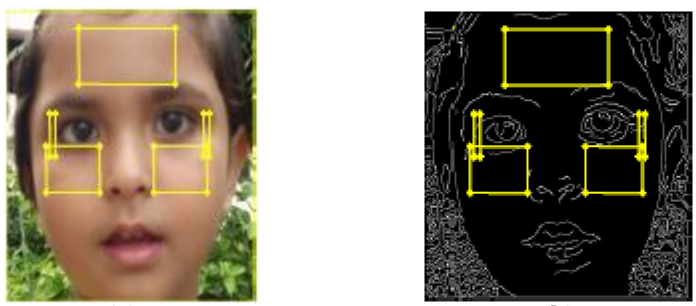
(a) (b) (c) (d)

Figure 4.7: Geometric Distance between (a) the two eyes (b) eye to nose (c) eye to chin (d) eye to lip

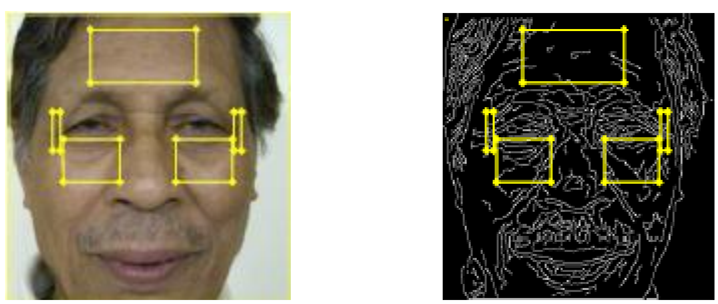
- ***Wrinkle Feature***

After calculating the geometric distance features, canny edge detection algorithm is used for extracting the wrinkles from the facial image which gives the binary image of a face with the wrinkle edges as shown in Figure 4.8. In that binary image, black pixel is represented by 0 and white pixel is represented by 1, therefore the sum of pixels is more with more presence of wrinkle. Fifth feature is calculated as F5 using the wrinkle feature such as the upper portion of the cheeks, eye-corner region and forehead region.

F5 = (sum of pixels in left cheek region / number of pixels in the left cheek region) + (sum of pixels in right cheek region / number of pixels in the right cheek region) + (sum of pixels in forehead portion / number of pixels in forehead portion) + (sum of pixels in left eye-corner region / number of pixels in left eye-corner region) + (sum of pixels in right eye-corner region / number of pixels in right eye-corner region)



(a) (b)



(c) (d)

Figure 4.8: Wrinkle region Feature using Canny Edge Detection

4.3. Classification

As the last step of the age-group prediction, it is extremely important to choose the appropriate model of classifier. So, two different classifiers are used such as Support Vector Machine (SVM) and K-Nearest Neighbor (described in chapter 1) for the prediction of age-group because the SVM has the strong capability of learning a pattern and also a strong ability of non-linear classification. Also, K-NN is an easy and fast way to implement and for k-NN, subject is classified on the basis of its nearest ‘k’ neighbors.

After preprocessing and extracting the features of the image from the above steps, firstly, training dataset is created from the feature extracted facial images and then training dataset is put into the classifier to train SVM or K-NN model. When a classifier gets trained, test dataset is then passed to the classifier. Finally, SVM or K-NN classifier is applied that classifies the test dataset images in one of the three different groups such as young, adult and old as shown on Figure 4.9.

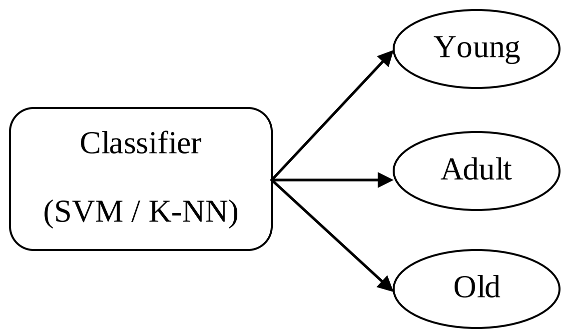


Figure 4.9: Age-Group Classification

Chapter 5
Experiment and Results

This project is implemented on 32-bit windows 7 system having 4GB of RAM. All the implementation work is done under MATLAB 2013a as a framework.

5.1. Data Sources

Now a day, the social media or networking are the only part of the resources. Search engine such as Google, Yahoo, Bing, etc. can locate more resources according to the requirement. Moreover, users on social networking sites are mainly the youngsters. Therefore, in the proposed model, dataset of facial images have been collected from internet using search engine and also self-build database of facial images is used. For this experiment, it has been established that dataset is large, so a random division of dataset for training and testing purpose ensures the accurate prediction. For example, division can be 70% data as training set and remaining data as testing set.

5.2. Experimental Result

For executing the proposed method, a small data set 180 images has been taken that contains 60 images each for young, adult and old where 120 images (40 from each group) are used as a training set and remaining 60 images (20 for each group) are used for test set. The training dataset is sent to the classifier which is then used to train the SVM model or K-NN model. Finally, the test dataset is passed into the classifier and applied either SVM classifier model or K-NN classifier model that classifies the test dataset images into one of the three different groups such as young, adult and old.

5.2.1 SVM Classification Result

The identification results obtained by the SVM classifier for the test dataset are shown in table 5.1 and also Confusion matrix, Regression graph, and Receiver operating characteristics are used for displaying the achieved results.

Table 5.1: SVM Identification Results

Group	Identification Results			
	Child	Adult	Old	Identification Rate
Child	17	0	3	85%
Adult	0	19	1	95%
Old	0	0	20	100%

So, the average identification rate achieved using SVM classifier = (85% + 95% + 100%) / 3 = 93.3%.

- *Confusion Matrix* – It takes the target data array, and the output data array in a 1-of-N form as a input arguments like ‘plotconfusion(target, output)’ and generates a confusion matrix plot where class 1, class 2 and class 3 indicates the young class, adult class and old class respectively.
- *Regression Graph* – It simply takes a target data array and the output data array as a input arguments like ‘plotregression(target, output)’ and generates a regression graph plot where ‘R’ indicates the performance rate achieved from the experiment.
- *Receiver operating characteristics* – This characteristics takes the target data array in a 1-of-N form, and the output data array like ‘plotroc(target, output)’ and produces a receiver operating characteristics plot where class 1, class 2 and class 3 indicates the young class, adult class and old class respectively.

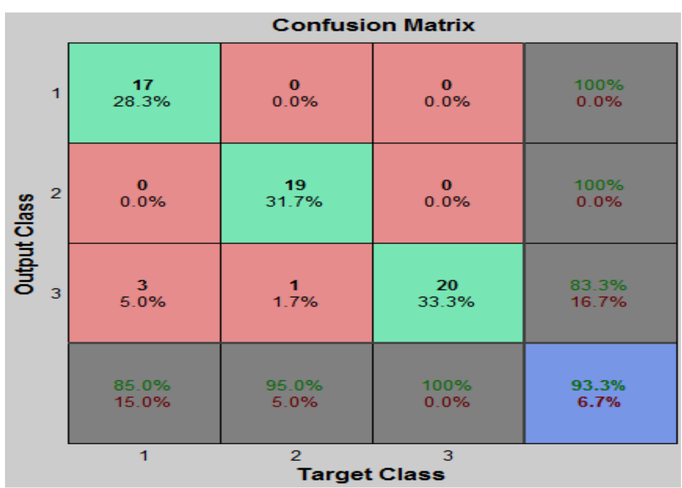


Figure 5.1(a): Confusion Matrix based on SVM

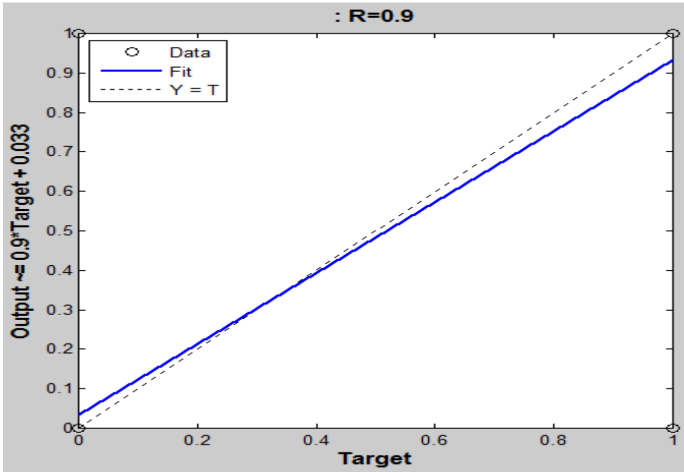


Figure 5.1(b): Regression Graph based on SVM

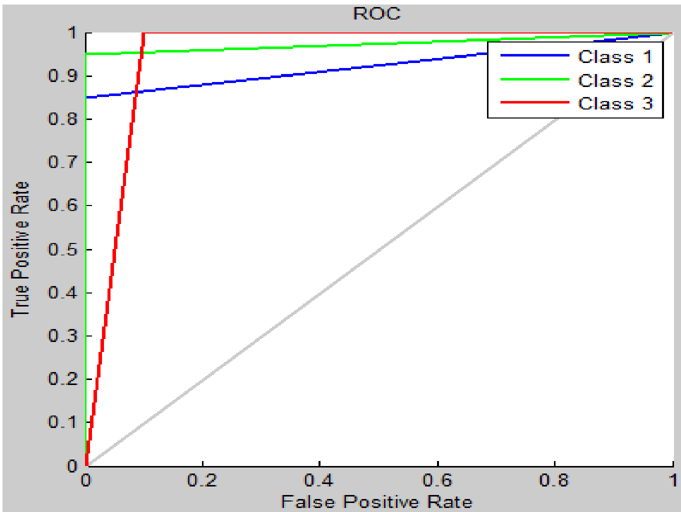


Figure 5.1(c): Receiver operating characteristics based on SVM

5.2.2 k-NN Classification Result

The identification results obtained by the k-NN classifier for the test dataset are shown in table 5.2 and similarly, used Confusion matrix, Regression graph, and Receiver operating characteristics for displaying the achieved results.

Table 5.2: k-NN Identification Results

Group	Identification Results			
	Child	Adult	Old	Identification Rate
Child	19	0	1	95%
Adult	1	19	0	95%
Old	0	0	20	100%

So, the average identification rate achieved using k-NN classifier = (95% + 95% + 100%) / 3 = 96.7%.

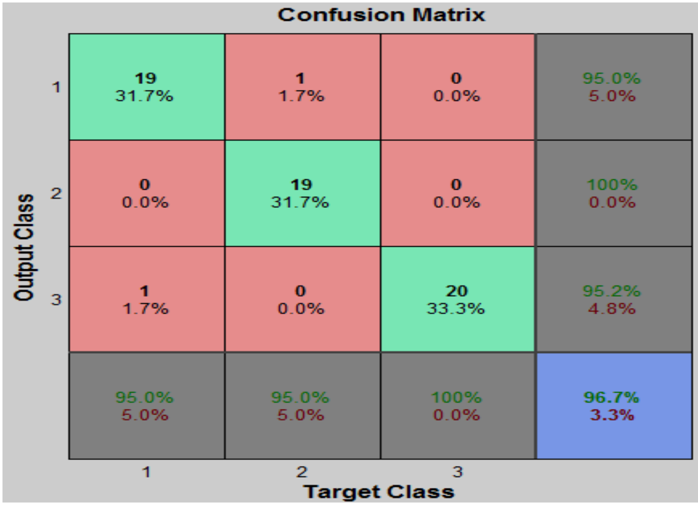


Figure 5.2(a): Confusion Matrix based on k-NN

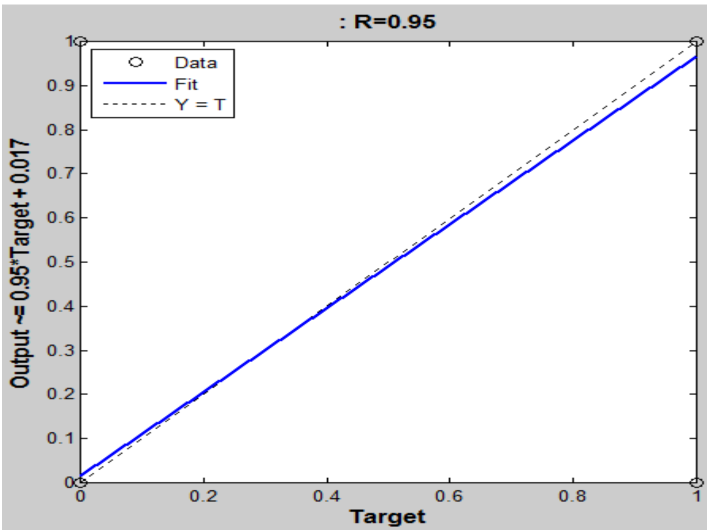


Figure 5.2(b): Regression Graph based on k-NN

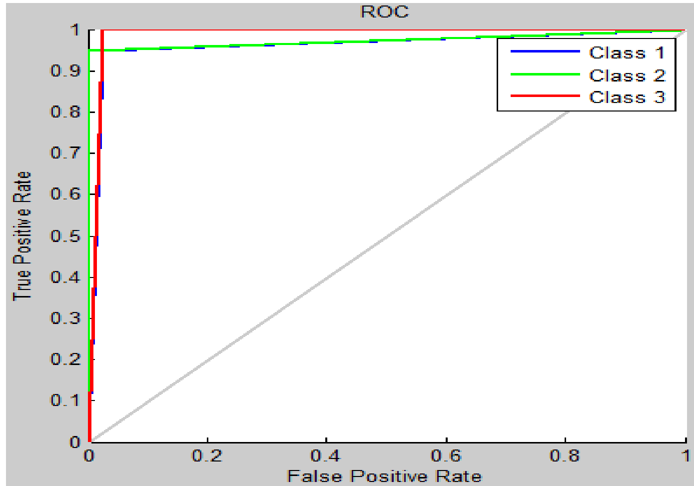


Figure 5.2(c): Receiver operating characteristics based on k-NN

From the above results obtained from SVM model and K-NN model, it has been observed that the achieved identification rate of age-group prediction using SVM is 93.3% and using k-NN is 96.7%. So, it can be concluded that the k-NN classifier produces better results than the SVM classifier for the age-group prediction.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

In this work, age-group prediction model has been proposed that classifies the age into three different groups, including child, adult and old from the input facial images. From this research work, it can be concluded that the proposed method improves significantly over existing age prediction methods. Proposed system processes include preprocessing of input image, extraction of features, train the classifier by sending extracted features to the SVM or K-NN classifier and finally, testing is done for the test data by passing it to classifier in order to obtain the results. From the experimental results achieved, it can be concluded that the k-NN classifier produces better results than the SVM classifier for the age-group prediction.

6.2 Recommendation and Future Scope

From the experiments and summons encountered in this research, it has been able to observe some of the certain aspects that could not be accomplished within the extent of this work and therefore these can be suggested for the future work. From the results obtained, it is recommended that proposed age-group prediction algorithm could be effectively employed in many applications such as Age-Specific Human Computer Interaction, web application in order to prevent the under-age from, not to have access or from buying the adult contents or materials, and Security and Surveillance system for locating animals.

In the future, the work will focus on involving other facial features like Texture features; Gabor features, etc. and classifying the age-groups in more the three categories. As we know, security and surveillance system works mostly with the video images, the work would also focus on testing the video images against the still images used in this work.

References

[1] Tonchev, K., et al. "Human age-group classification of facial images with subspace projection and support vector machines." *Intelligent Data Acquisition and Advanced Computing Systems (IDAACS), 2011 IEEE 6th International Conference on*. Vol. 1. IEEE, 2011.

[2] Guo, Guodong, et al. "A probabilistic fusion approach to human age prediction."*Computer Vision and Pattern Recognition Workshops, 2008. CVPRW'08. IEEE Computer Society Conference on*. IEEE, 2008.

[3] William, K. Pratt, “Digital Image Processing”, Fourth Edition, A John Wiley & Sons Inc. Publication, pp.465-529, 2007.

[4] J. Tumblin and G. Turk, “LCIS: A Boundary Hierarchy for Detail-Preserving Contrast Reduction,” in *Proceedings of ACM 26th Annual Conference on Computer Graphics and Interactive Techniques,* New York, 1999, pp. 83-90.

[5] http://en.wikipedia.org/wiki/Viola%E2%80%93Jones_object_detection_framework

[6] H. Drucker, C.J.C. Burges, L. Kaufman, A. Smola, and Vladimir Vapnik. Support vector regression machines. Advances in Neural Information Processing Systems, 9:155{161, 1997.

[7] Y. H. Kwon and N. Vitoria Lobo. “Age classification from facial images”, *Computer Vision and Image Understanding Journal*, **vol. 74, no. 1**, pp. 1-21, (1999).

[8] W. B. Horng, C. P. Lee, C. W. Chen. “Classification of age groups based on facial features”, *Tam kang Journal of Science and Engineering, vol***. 4**, pp. 183–192, (2001).

[9] J. Hayashi, M. Yasumoto, H. Ito, Y. Niwa, and H. Koshimizu, “Age and Gender Estimation from Facial Image Processing,” *Proceedings of the 41st SICE Annual Conference*, Volume: 1, Page(s): 13 -18, Aug. 2002.

[10] A. Lanitis, “On the significance of different facial parts for automatic age estimation,” *14th International Conference on Digital Signal Processing*, Volume: 2, Page(s): 1027 -1030, July 2002.

[11] Chen, Yi-Wen, et al. "Image-based age-group classification design using facial features." *System Science and Engineering (ICSSE), 2010 International Conference on*. IEEE, 2010.

[12] Tonchev, K., et al. "Human age-group classification of facial images with subspace projection and support vector machines." *Intelligent Data Acquisition and Advanced Computing Systems (IDAACS), 2011 IEEE 6th International Conference on*. Vol. 1. IEEE, 2011.

[13] Khryashchev, Vladimir, et al. "Age estimation from face images: challenging problem for audience measurement systems." *Open Innovations Association (FRUCT16), 2014 16th Conference of*. IEEE, 2014.

[14] Li, Weixing, et al. "Facial age classification based on weighted decision fusion." *Control Conference (CCC), 2014 33rd Chinese*. IEEE, 2014.

[15] Guo, Guodong, et al. "A probabilistic fusion approach to human age prediction."*Computer Vision and Pattern Recognition Workshops, 2008. CVPRW'08. IEEE Computer Society Conference on*. IEEE, 2008.

[16] Günay, Asuman, and Vasif V. Nabiyev. "Automatic age classification with LBP." *Computer and Information Sciences, 2008. ISCIS'08. 23rd International Symposium on*. IEEE, 2008.

[17] Hajizadeh, Mohammad Ali, and Hossein Ebrahimnezhad. "Classification of Age Groups from Facial Image Using Histograms of Oriented Gradients." *Machine Vision and Image Processing (MVIP), 2011 7th Iranian*. IEEE, 2011.

[18] Izadpanahi, Shima, and Onsen Toygar. "Geometric feature based age classification using facial images." *Image Processing (IPR 2012), IET Conference on*. IET, 2012.

[19] Luo, Ren C., Li Wen Chang, and Shih Che Chou. "Human age classification using appearance images for human-robot interaction." *Industrial Electronics Society, IECON 2013-39th Annual Conference of the IEEE*. IEEE, 2013.

[20] Li, Weixin, Yunhong Wang, and Zhaoxiang Zhang. "A hierarchical framework for image-based human age estimation by weighted and OHRanked Sparse Representation-based classification." *Biometrics (ICB), 2012 5th IAPR International Conference on*. IEEE, 2012.

[21] Thukral, Pavleen, Kaushik Mitra, and Rama Chellappa. "A hierarchical approach for human age estimation." *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*. IEEE, 2012.

[22] Nithyashri, J., and G. Kulanthaivel. "Classification of human age based on Neural Network using FG-NET Aging database and Wavelets." *Advanced Computing (ICoAC), 2012 Fourth International Conference on*. IEEE, 2012.

[23] Yang, Xi, et al. "Facial age estimation from web photos using multiple-instance learning." *Multimedia and Expo (ICME), 2014 IEEE International Conference on*. IEEE, 2014.

[24] Liu, Li, Jianming Liu, and Jun Cheng. "Age-group classification of facial images." *Machine Learning and Applications (ICMLA), 2012 11th International Conference on*. Vol. 1. IEEE, 2012.

[25] Lee, Seung Ho, and Yong Man Ro. "Local age group modeling in unconstrained face images for facial age classification." *Image Processing (ICIP), 2014 IEEE International Conference on*. IEEE, 2014.

[26] Ueki, Kazuya, Teruhide Hayashida, and Tetsunori Kobayashi. "Subspace-based age-group classification using facial images under various lighting conditions." *Automatic Face and Gesture Recognition, 2006. FGR 2006. 7th International Conference on*. IEEE, 2006.

[27] Chao, Wei-Lun, Jun-Zuo Liu, and Jian-Jiun Ding. "Facial age estimation based on label-sensitive learning and age-oriented regression." *Pattern Recognition*46.3 (2013): 628-641.

List of Publications

1. Madhur Jain and Ashutosh Mishra, “SVM based Age Group Estimation of Facial Images”, accepted at 1st International Conference on Next Generation Computing Technologies (NGCT-2015), UPES, Dehradun, IEEE, 2015.

Video Link

http://youtu.be/N28lhwm0TzE