Human Gender And Age Detection from Facial Images Using Convolution Neural Network

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Abstract. Human gender detection which is a part of facial recognition has received extensive attention because of it's different kind of application. Previous research works on gender detection have been accomplished based on different static body feature for example face, eyebrow, hand-shape, body-shape, finger nail etc. In this research work, we have presented human gender classification using Convolution Neural Network (CNN) from human face images as CNN has been recognised as best algorithm in the field of image classification. To implement our system, at first a pre-processing technique has been applied on each image using image processing. The pre-processed image is passed through the Convolution, RELU and Pooling layer for feature extraction. A fully connected layer and a classifier is applied in the classification part of the image. To obtain a better result, we have implemented our system using different optimizers and also have used k fold cross-validation as deep learning approach. The whole method has been evaluated on two dataset collected from Kaggle website and Nottingham Scan Database. The experimented result shows a highest accuracy which is 97.44% using Kaggle dataset and 90% accuracy using Nottingham Scan Database.

Keywords: Convolution neural network · Convolution · RELU · Pooling layer · Fully connected layer · K-fold cross-validation · Optimizers · Kaggle datset · Nottingham Scan Database

1 Introduction

Gender detection plays a significant role in modern technology. The detection of gender has many dynamic applications such as social interaction, security maintenance and surveillance, video games, human-computer interaction, criminal identification, mobile application, commercial development, monitoring application etc. It has occupied a great space in the field of facial recognition. The main

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purpose of gender detection is to differentiate male and female based on different features of human.

In recent years, various research papers have been published regarding human gender classification using different methods. Human gender can be classified using different features such as face, eyebrow [12], hand-shape [5], body-shape [8], finger nail [32]. Among these, the majority of the gender detection research have been accomplished using face images. The feature extraction is classified into two categories [7], namely geometric based and appearance based.

In the geometric based feature extraction, different facial components or feature points are extracted which mainly represents the face geometry [11]. In the appearance based feature extraction, the features are extracted applying image filter the whole image or particular component of an image [11]. The appearance based feature extraction has an advantage over the geometric based feature extraction. In the geometric based feature extraction, only some fixed points of face image are used where in the appearance based feature extraction, information is extracted from the whole face image. The training process of classifying gender includes several methods such as Support Vector Machine (SVM), Principal Component Analysis (PCA), and Neural Networks (NN) [7]. However, in the field of image classification the Convolution Neural Network (CNN) has been proved to perform as best algorithm comparing with other machine learning algorithms [3,27]. The filters are optimized through automated learning in CNN [6,33] whereas they are hand-engineered in other traditional algorithms. This is a major advantage of CNN as it is independent of human intervention in feature extraction. Moreover, while using an algorithm with pixel vector, a lot of spatial interaction between pixels are lost. A CNN can effectively use adjacent pixel information by convolution and then uses a prediction layer at the end.

Our main purpose of this research is to detect human gender from facial images where we have used an image processing technique for appearance based feature extraction and Convolution Neural Network (CNN) for the classification of human gender. In this regard, at first we have applied an image processing technique where we have converted the face image into a two dimensional array where the values of the array indicates the pixel values of the image. After that, all the pixel values have been divided by 255 so that all the values of the array come to a range between 0 to 1. This is done to reduce the difference among the values.

After this pre-processing step, a machine learning algorithm called Convolution Neural Network is applied for the classification of gender using a compact variant of VGGNet architecture on 2 dataset which are Kaggle dataset and Nottingham Scan Database. After implementation, a highest accuracy 97.44% has been gained using Kaggle dataset and 90% has been gained using Nottingham Scan Database. The significant contributions of our research are:

1. Performance comparison has been shown among different optimizers.
2. K-fold cross validation has been applied as a deep learning approach.
3. Performance comparison has been shown among different activation function.
4. Dataset has been splitted into different ratio to gain a best accuracy.

The next sections of the paper are arranged accordingly: Sect.2 contains the previous works regarding gender classification. Section3 describes the methodology where Convolution Neural Network is discussed broadly. Section4 shows experimental setup where the experimental tools used in implementing our system has been stated. Section5 is about the result and discussion and finally in Sect.6 conclusion and future work has been discussed.

2 Literature Review

In the field of image processing and machine learning, a lot of research work has been done on human gender estimation. In this section, a brief overview of previous work on human gender estimation has been presented.

Lian HC [20] obtained an accuracy of 94.81% applying local binary pattern (LBP) and SVM with polynomial kernel on the CAS-PEAL face database. According to this method, a good accuracy can be achieved if the block size for the LBP operator is correctly selected, which is really a difficult task. Li et al. [19] performed the classification of gender utilizing only five facial features (eyes, nose, mouth, brows, forehead). One drawback of this research is that the feature extraction method they have used is affected by complex backgrounds. Saeed Mozaffari, Hamid Behravan and Rohollah Akbari [23] used geometric based feature for male female classification where they have used AR and Ethnic dataset containing 126 frontal images in each dataset. Here they have achieved 80.3% and 86.6% accuracy respectively. In [10] a texture based local binary pattern has been used for feature extraction and as classification algorithm na¨ıve Bayes, ANN and linear SVM has been applied. They achieved 63% accuracy with only 100 face images that has been collected from Nottingham Scan database which is quite low. Sajja, T. K., Kalluri, H. K. [28] have worked on gender classification from face images using LBP, SVM and Back Propagation. In this research they have used ORL dataset which contains 400 images and Nottingham Scan database which contains 100 images. After implementation they gained 100% accuracy for ORL dataset and 71% accuracy for Nottingham Scan database respectively. The work in [24] showed a high classification accuracy of 99.30% using SUMS face database. In this work, the researchers applied 2D-DCT feature extraction, Viola and Jones face detection and the K-means nearest neighbor (KNN) algorithm as classifier. Being a compute-intensive algorithm, 2D-DCT is not suitable for realtime applications. Using principal component analysis (PCA), researchers in [30] processed the face image to reduce the dimensionality. After that, a good subset of eigenfeatures has been selected using genetic algorithm (GA). Here, they reported an average error rate of 11.30%. The main drawback of this method is that, the GA exhibits high computational complexity. Althnian et al. [4] used hand crafted and fused features for face gender recognition where they have used both SVM and CNN and gained best accuracy 86.60% using CNN which can be improved further. Serna et al. [29] worked on gender detection using VGG and ResNet where they analyzed how bias affects deep learning. They divided the images into 3 ethnic groups and also experimented on an unbiased group. Here they achieved best average accuracy 95.27% for unbiased group using VGG and 95.67% Biased group 3 using ResNet.

Deviating from only facial based gender recognition, some researchers have worked on estimating human gender from different body parts for example body shape, eyebrow, hand shape, finger nail etc. Dong, Yujie & Woodard, Damon [12] approached a new technique where they classified gender using eyebrow shape. For classification MD, LDA and SVM were used in this paper and they gained 96% and 97% accuracy for MBGC and FRGC dataset respectively. In [5] they investigated human gender from hand shape from a small dataset containing 40 images and they achieved 98% accuracy. As classification algorithm Score-level fusion and LDA have been applied here. Honga´Lim et al. [32] presented a novel method for gender classification using finger nail with 80 samples donated by 40 people. With the use of PCA and SVM as classification algorithm, they showed about 90% accuracy in this research.

So considering the whole literature review, it is clear that an improvement in gender classification is needed. The main disadvantages of the above gender classification research works is that, the feature extraction and the classification are performed separately. To obtain an optimum pre-processing and feature extraction design, prior knowledge is needed here. In case of CNN which is a multilayer neural network model [21,22], it can optimize filters through automated learning where it is independent of prior knowledge which demonstrate a superior performance can be achieved using CNN.

3 Methodology

In our proposed system, we have utilized a CNN (Convolutional Neural Network) architecture. CNN which is a deep learning algorithm is capable of distinguishing images from their characteristics [1,9,14]. CNN is generally used for image analysis, image segmentation, image classification, medical image analysis, image and video recognition, etc. [2,13]. In this research, at first we have applied an image processing technique as pre-processing on images to transform the raw data into an efficient and useful format. Later, the CNN architecture has been applied. Here, it has been decomposed into two parts:

- Feature Extraction
- Classification

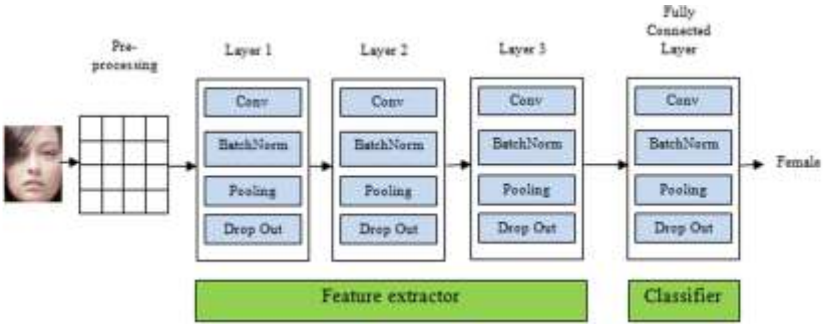


Fig.1. Network architecture

The convolution and the pooling layers performs the feature extraction of image which actually extract information from input for decision making. Finally, fully connected layer performs as the classification part. Our basic network architecture has been illustrated in Fig.1.

3.1 Dataset

In the field of gender estimation, there are several global datasets used in different research works. In this paper, we have used two global datasets so that we can show the comparison of the result achieved using different datasets. One of the two datasets is collected from kaggle website and the other is Nottingham Scan database.

Kaggle Dataset. The CELEBA aligned data set has been used in kaggle dataset to provide image. This dataset is of good quality and large. Here, the images are separated into 1747 female and 1747 male as training images, 100 male and 100 female as test image and 100 male, 100 female as validation images. A face cropping function using MTCNN has been applied here to crop the images so that only face images are included here. In Fig.2 a sample of Kaggle Database have been shown.

Fig.2. Sample of Kaggle Dataset

Nottingham Scan Database. Nottingham Scan database is comprise of 100 human faces where half of the images are of male and half images are of female.

The format of images used in this database is .gif format. 438×538 pixel size image hase been used here with 256 a gray-levels. As per our requirement, the images have been converted to .jpg format from .gif format. In Fig.3 a sample of Nottingham Scan Database have been shown.

3.2 Pre-processing

Pre-processing of image generally removes low frequency background noise, normalizes the intensification of the individual practical image, removes reflection of light to get rid of the image noise, and prepares the face image to better feature extraction. In our system, we have first resized the images into 96×96 dimension. Then We have converted the image to an array of pixel value. Each pixel value of the array is converted to float and divided by 255.0 so that all the pixel values comes to a range between 0 to 1. In Fig.4, the whole pre-processing system has been illustrated.

Fig.3. Sample of Nottingham Scan database

3.3 Feature Extraction

In Convolutional Neural Network (CNN), the feature extraction is performed by the Convolution and the Pooling layer. In our proposed system these layers are defined as follows:

1. The convolution layer contains 32 filters with a 3 × 3 kernel. Here RELU is used as the activation function followed by batch normalization.
2. The POOL layer uses a 3 × 3 pool size to reduce spatial dimension from 96 × 96 to 32 × 32. A dropout is used in our network architecture which disconnects nodes arbitrarily from layer to layer.
3. Next the convolution and ReLU layers are applied twice before applyinganother POOL layer. This operation of multiple convolutional and ReLU layers allow to learn a richer set of features. Here-

  - The filter size is being increased from 32 to 64. As we go deep into thenetwork, we will learn the filters more.
  - The max pooling size is decreased from 3 × 3 to 2 × 2 so that spatial dimensions don't get reduced too quickly. Dropout is again performed at this stage.

4. Again the convolution and ReLU layers is applied twice before applyinganother POOL layer. The filter size is increased to 128. And 25% dropout of the nodes is executed in this step for the reduction of over fitting.

3.4 Classification

Fully Connected and RELU operation is performed and a sigmoid classifier is used for classification. Here-

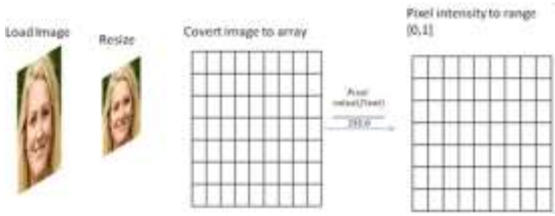


Fig.4. Pre-processing steps

1. RELU and batch normalization with dense (1024) defines the fully connectedlayer where dropout is executed for the last time. This time 50% of the node is being dropped during training.
2. Finally, sigmoid function is used as classifier to return the predicted probabilities for each class label.

$$Sigmoid(x) = \frac{1}{1 + e^{-\theta^T x}}$$

In Fig.5 the whole schematic diagram of our network architecture has been provided.

4 Experimental Setup

Our system has been implemented using python programming language. Matplotlib, keras, numpy libraries has been used for system implementation. Keras provides some built in functions such as activation functions, optimizers, layers etc. Tensorflow has also been used as the system backend. In Table 1, the experimental tools used in this system implementation has been showed.

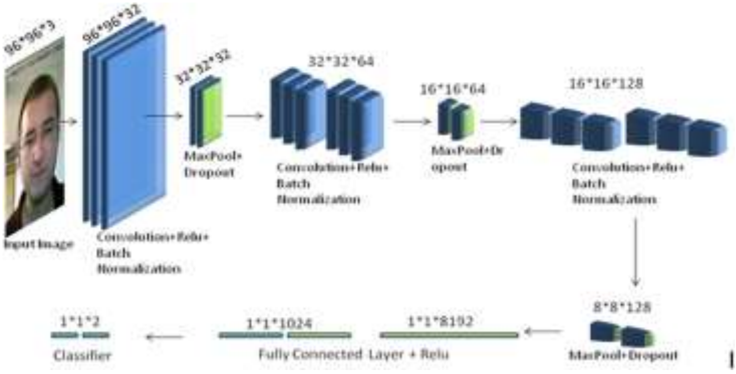


Fig.5. A full schematic diagram of network architecture

Table 1. Experimental tools

Name	Experimental tool
Hardware	i. Microsoft Windows 8.1 pro ii. Processor Intel (R) core (TM) i3-5005U, 4 GB RAM
Software	Spyder (Python3.7)
Programming Language	Pythonn
Method implementation	i. Keras 2.2.4 ii. Tensorflow 1.15.0

5 Result and Discussion

As stated in earlier section, we have used two dataset to evaluate our model. For both dataset, we have implemented our model using different optimizers so that best accuracy can be obtained. After that we have trained our model using 5 fold cross validation as deep learning approach.

5.1 Comparison of Result Among Different Optimizers and Activation Functions

Table2 shows the training and testing accuracy for different optimizers for both Kaggle and Nottingham Scan Database.

As we can see using Kaggle dataset, we have achieved satisfactory accuracy using Adam, Adamax, RMSprop and Adagrad optimizer which is above 90%. Using SGD and Adadelta optimizer the accuracy gained less comparing with the others. Among all of these, the best accuracy has been gained using the Adam optimizer. For Nottingham Scan Database, the Adam optimizer shows the best accuracy and also it maintains a good balance between training and testing accuracy. So, we can say that for both dataset the best accuracy is obtained using adam optimizer.

Table 2. Accuracy using different optimizers

Optimizers	Kaggle Dataset	Nottingham Scan Dataset

	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Adam	98%	95%	90.62%	90%
Adamax	96%	94%	78.12%	85%
RMSprop	97%	93%	93.75%	65%
Adagrad	91%	93%	87.50%	85%
SGD	84%	86%	53.12%	82.50%
Adadelta	70%	76%	40.62%	65%

Figure6 and 7 shows Loss/Accuracy curve using Adam optimizer for Kaggle dataset and nottingham scan database respectively.

In Table3, we have shown the accuracy acquired by splitting the dataset into different ratio. Here, the best training and testing accuracy we have achieved by splitting both dataset into 80% training and 20% testing which is 98.09% training accuracy and 95% testing accuracy for Kaggle dataset and 87.50% training accuracy and 80.50% testing accuracy for Nottingham Scan Dataset.

Table 3. Accuracy comparison of splitting dataset

Split Ratio	Kaggle Dataset		Nottingham Scan Dataset	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
60%–40%	96.49%	93.63%	80.77%	80%
70%–30%	96.63%	93.03%	75.67%	80%
80%–20%	98.09%	95%	87.50%	80.50%
90%–10%	93.41%	94%	80.62%	75%

Table4 shows the result of our system implementation using different activation functions to see which activation function generates the best result. In this case we have considered the splitting ratio as 80%-20% as we achieved a satisfactory accuracy by splitting the dataset into 80% training and 20% testing. Here as we can see, the sigmoid function results the best for each dataset. Softmax function performs well for Kaggle dataset but it shows overfitting problem in Nottingham Scan Dataset. On the other hand, Relu activation function shows a poor accuracy for both dataset.

5.2 K-Fold Cross Validation

Cross validation is a re-sampling method which is used to evaluate machine learning models on a limited data sample. Here we have implemented our model

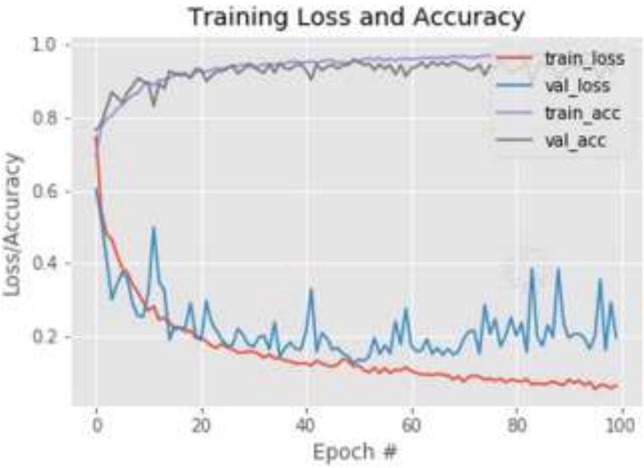


Fig.6. The Loss vs Accuracy curve using Adam optimizer for Kaggle dataset

Table 4. Accuracy using different activation function

Activation function	Kaggle Dataset		Nottingham Scan Dataset	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Sigmoid	98%	95%	90.62%	90%
Softmax	93.20%	87.98%	93.10%	60%
Relu	28.35%	26.20%	28.12%	50%

using K-fold cross validation as a deep learning approach on both Kaggle Dataset and Nottingham Scan Database. We have chosen the value of k=5 here as 5 fold cross-validation.

Table5 shows the result of our model using 5 fold cross-validation and also the average accuracy and the best accuracy achieved after the 5 fold cross-validation. As we can see, the average accuracy and the best accuracy we have achieved are respectively 95.06% and 97.44% for Kaggle Dataset and 83.50% and 90% for Nottingham Scan Database.

In Table6, we have shown the comparison of our proposed method with two existing method where Nottingham Scan Database have been used. Datta et al. [10] applied texture based LBP for feature extraction. Artificial Neural Network (ANN), Na¨ıve Bayes, Linear SVM algorithms have been applied for classification. They have achieved a highest accuracy of 63% using ANN classification algorithm. In [28], the researchers used a combination of LBP and SVM where they achieved 55% accuracy and used a combination of LBP and NN where they

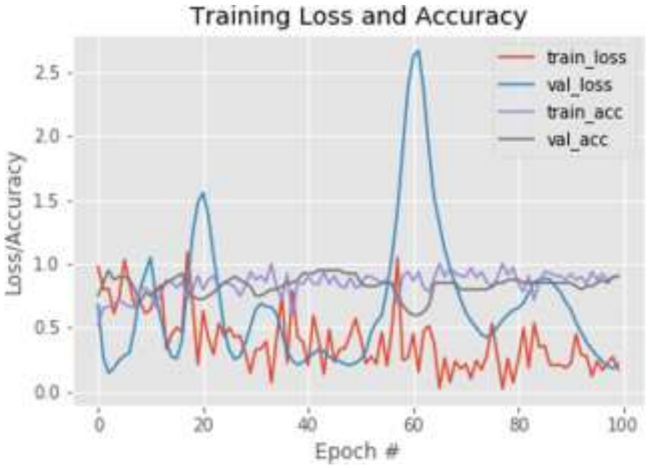


Fig.7. The Loss vs Accuracy curve using Adam optimizer for Nottingham Scan database

Table 5. Accuracy using K-fold cross validation

Fold	Kaggle Dataset		Nottingham Scan Dataset	
	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
1	98.07%	93.92%	90.62%	90%
2	97.62%	94.28%	96.88%	82.85%
3	98.09%	97.44%	87.50%	77.50%
4	96.93%	94.28%	90.62%	85%
5	97.44%	95.42%	90%	82.50%
Average Accuracy	97.51%	95.06%	90%	83.50%
Best Accuracy	98.09%	97.44%	96.88%	90%

Table 6. Comparison of the proposed approach with existing method

Serial No	Reference	Method	Database	Accuracy
1	Datta et al. [10]	LBP+ANN	Nottingham Scan Database	63%
2	Sajja, T.K. [28]	LBP+NN	Nottingham Scan Database	71%
3	Our proposed method	CNN	Nottingham Scan Database	83.5%

achieved 71% from the Nottingham Scan database. But in our proposed method, we have got a best accuracy 90% using CNN model with 5 fold cross-validation and the average accuracy of the 5 folds is 83.50%.

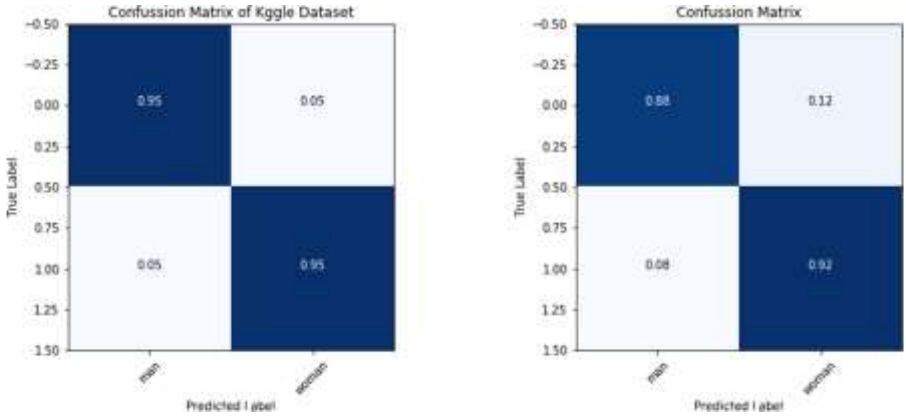


Fig.8. Confusion matrix of 5-fold cross-validation on Kaggle dataset and Nottingham Scan Database

Figure8 shows the confusion matrix of 5-fold cross-validation on Nottingham Scan Database and Kaggle Dataset respectively.

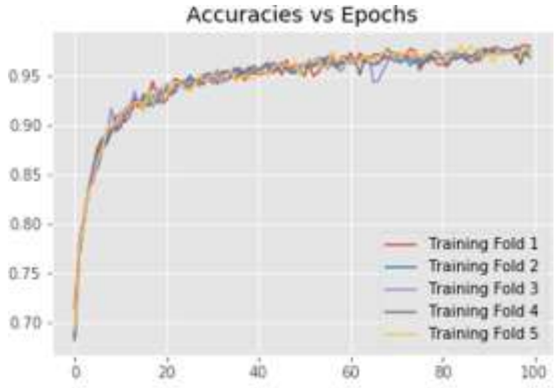
Figure9 shows accuracy vs epoch curve using 5 fold cross-validation for kaggle dataset and nottingham scan database respectively. As we can see here, we have achieved a satisfactory accuracy after 100 epoch.

5.3 Performance Metrics

Researchers generally evaluate the overall performance and also the efficiency of machine learning algorithms using these factors [26]. In our model we have evaluated performance metrics to understand how well our model is performing on given dataset. In this study, the performances have been evaluated based on three criteria- Recall, Precision, F1-score. In Table7, the comparison of the performance metrics for both datasets are shown.

Table 7. Different parameters

Performance matrices	Kaggle Dataset			Nottingham Scan Dataset		
	Man	Woman	Macro Average	Man	Woman	Macro Average
Precision	0.95	0.95	0.95	0.88	0.92	0.90
Recall	0.95	0.95	0.95	0.88	0.92	0.90
F1-score	0.95	0.95	0.95	0.88	0.92	0.90



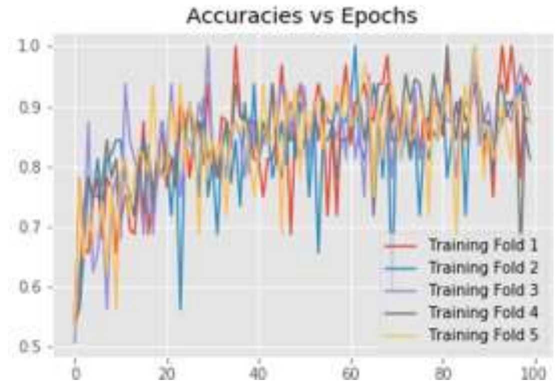


Fig.9. The Accuracy vs Epoch curve using 5 fold for Kaggle dataset and Nottinghum scan database

***Abstract:** Gender is a central feature of our personality still. In our social life it is also an significant element. Artificial intelligence age predictions can be used in many fields, such as smart human-machine interface growth , health, cosmetics, electronic commerce etc. The prediction of people's sex and age from their facial images is an ongoing and active problem of research. The researchers suggested a number of methods to resolve this problem, but the criteria and actual performance are still inadequate. A statistical pattern recognition approach for solving this problem is proposed in this project.Convolutionary Neural Network (ConvNet / CNN), a Deep Learning algorithm, is used as an extractor of features in the proposed solution. CNN takes input images and assigns value to different aspects / objects (learnable weights and biases) of the image and can differentiate between them. ConvNet requires much less preprocessing than other classification algorithms. While the filters are hand-made in primitive methods, ConvNets can learn these filters / features with adequate training.In this research, face images of individuals have been trained with convolutionary neural networks, and age and sex with a high rate of success have been predicted. More than 20,000 images are containing age, gender and ethnicity annotations. The images cover a wide range of poses, facial expression, lighting, occlusion, and resolution.*

***Keywords:** Facial Images; Gender Prediction; Age Prediction; Convolutional Neural Network; Deep Learning.*

6 I. INTRODUCTION

The aim is to predict the age of individuals using image data sets. An growing number of applications, especially after the increase in social networks and social media, are being concerned with automatic age classification. Age and gender are the two most fundamental facial qualities in social interaction. In smart applications, such as access control, human computer interaction, enforcement, marketing intelligence and visual supervision, etc, it is important to make age evaluations using one facial image.Machine learning: supervised learning, image recognition, and deep learning: a groundbreaking neural network and profound learning are the most common technologies used in this project. Supervised learning can be described as a machine learning technique in which the input is mapped to the output using input-output pair training data. TensorFlow is an open-source library used for math, data flow and specific machine learning applications.

Convolutional Neural Network (CNN) is one of the most prevalent algorithms that has gained a high reputation in image feature extraction.Age Classification using Convolutional Neural Networks:

A Convolutionary Neural Network (ConvNet / CNN) is a Deep Learning algorithm, which allows an input image to take on different aspects / objects and can be distinguished from one image (learnable weights and biases). ConvNet requires much less preprocessing than other classification algorithms. While the filters are hand-made in primitive methods, ConvNets can learn these filters / features with adequate training.The ConvNet architecture is similar to that of neurons in the human brain and was influenced by the Visual Cortex organisation. Within a limited area of the visual field known as the Receptive Field, only individual neurons respond to stimuli. The entire visual area is protected by a selection of these fields. About Dataset: a broad facial dataset of long age (range 0-116 years old) is a UTKFace data set. The data collection consists of more than 20,000 facial images with age, gender and ethnicity annotations.The images cover a wide range of poses, facial expression, lighting, occlusion, resolution .It can be used for a variety of tasks, for example face detection, age estimation, age progression, position of landmarks etc. The survey is focused on the age detection of the neural network (CNN) image dataset architecture. The problem may then be treated as a classification concern with 3 convolution layers and 2 completely interconnected layers with a final output layer. Estimating the exact age by regression is a challenging process. Age prediction systems have been growing rapidly in recent days thanks to its important modules and use for many computer vision applications, such as interaction between human and computer, safety systems and visual monitoring.The value of an age prediction is shown by several examples. For example, there is an age to get alcohol, drive vehicles, travel alone outside the country, smoke cigarettes, etc. The problem is, however, that human capacities are poor and unreliable in age prediction. So it would be necessary to reject underage individuals with computer vision systems. Hotels, airports, busses, casinos, government buildings, universities , hospitals, movie theatres, etc. are currently using automated age and gender prediction systems for improving protection and mitigating possible threats or poverty.Age prediction methods are also used in healthcare systems, knowledge recovery, academic studies, and Electronic Customer Relationship Management (ECRM) applications, which distributes customers to a range of aged groups including teenagers, teens, adults and senior citizens.

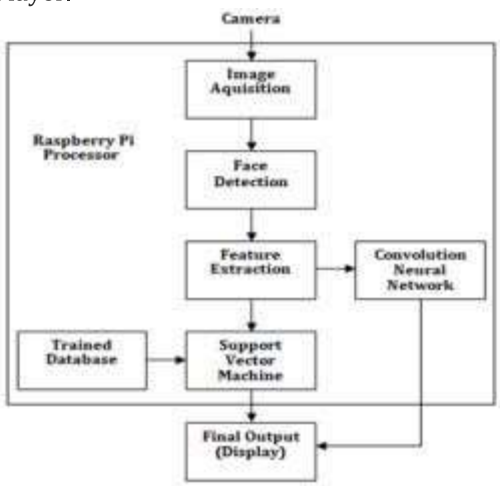
Moreover, it may allow businesses to identify products and services according to their age groups that increase income and make more money to collect those customers' daily lives information including behaviors, preferences, practices, 4 priorities etc.For instance, clothing shops that sell men's or women's fashion according to their age groups; restaurants wish to know the most common meals per group of age; many businesses want those audiences to advertise according to their age groups.

7 II. LITERATURE SURVEY

A new architecture for face image classification named unsupervised CNN was introduced by S. U. Rehman et al. [2]. A CNN that handles multitask (i.e. Facial detection and emotional classification) is made by merging CNN with other modules and algorithms. A hybrid deep CNN and RNN (Recurrent Neural Network) model was introduced by N. Jain et al. [4]. This model aims to improve the overall result of face detection. MI Facial Expression and JAFFE dataset were used to evaluate the model. A convolutional network architecture was proposed by G. Levi et al. [5] that classified the age with small amounts of data. The Audience Benchmark was used to train the model. A system in which a real time automatic facial expression system was designed was proposed by S. Turabzadeh et al. [6]. It was implemented and tested on an embedded device which could be the first step for a specific facial expression recognition chip for a social robot. MATLAB was first used to build and simulate the system and then it was built on an embedded system. The hardship of performing automatic prediction of age, gender and ethnicity on the East Asian Population using a Convolutional Neural Network (CNN) was explored by N. Srinivas et al. [3]. A fine-grained ethnicity has predictions based on a refined categorization of the human population (Chinese, Japanese, Korean, etc.). Previous results suggest that the most critical job is to predict the fine-grained ethnicity of a person, followed by age and lastly gender. An automated recognition system for age, gender and emotion was presented by A. Dehghan et al. [7] that was trained using deep neural network. At the ImageNet LSVRC-2010 contest, A. Krizhevskyetal. [8] presented a paper which suggested segregation of 1.2 million images into 1000 different categories with the help of a deep Convolutional neural network. The results which were obtained suggested that supervised learning can deliver exceptional accuracies. Some datasets have annotations on the face images which are not considered to be of any use for face recognition. Some papers have also used RNN but it is not applicable for our project as the RNN takes text or speech as an input whereas we required an image to be as the input. Hence, CNN is chosen over RNN for the sake of our project. Some papers also suggest the use of unsupervised CNN, but, for this project supervised learning is more appropriate. The UTKFace dataset is used as dataset for the project.

8 III. SOFTWARE REQUIREMENTS AND TECHNOLOGIES

To predict the age, we are going to use a convolutional neural Architecture of the network (CNN). This CNN uses 3 layers of convolution and 2 layers with one final output layer.



This problem can be interpreted rather than regression as a classification problem. It is a difficult job to estimate the exact age by means of regression. Simply by looking at the face even people can not predict age. In an age range, like 20-30 or 30-40, we will therefore seek to predict the age. It is hard to predict how a person's age depends on many factors from a single image.

9 ANALYSIS

Age detection is the process of *automatically* discerning the age of a person *solely* from a photo of their face. Typically, you'll see age detection implemented as a two-stage process:

1. **Stage #1:**Detect faces in the input image/video stream
2. **Stage #2:**Extract the face Region of Interest (ROI), and apply the age detector algorithm to predict the age of the person

9.1 For Stage #1, any face detector capable of producing bounding boxes for faces in an image can be used Once your face detector has produced the bounding box coordinates of the face in the image/video stream, you can move on to Stage #2 — identifying the age of the person.

9.2 MODULES

- **NUMPY**: Numpy is the most basic yet a powerful package for mathematical and scientific computing and data manipulation in python. It is an open source library available in python.
- **PANDAS**: Pandas library is used for data manipulation and analysis. It supports reading and writing excel spreadsheets, CVS's and whole lot of manipulation.
- **CV2**: OpenCV is a high performance library for digital image processing and computer vision, which is free and open source.
- **MATPLOTLIB**: Matplotlib is a plotting library for the python programming language and its numerical mathematics extensions in numpy.
- **OS**: The OS module in python provides a way of using operating system dependent functionality.
- **PIL**: PIL library is used for image manipulation in python. Using this library we are opening an image from dataset and resizing it.
- **SCIPY** : SciPy library contains different modules for optimization, linear algebra, integration and statistics.
- **X KERAS** : Keras is an open-source high-level neural network API, written in python. It allows easy and fast prototyping.
- **TENSORFLOW** : Tensorflow is a free and opensource software library for dataflow and differentiable programming across a range of tasks. It is used in neural networks.

9.3 TECHNOLOGIES

• **Image Processing:** Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too. Image processing basically includes the following three steps :

Importing the image via image acquisition tools;

Analysing and manipulating the image;

Output in which result can be altered image or report that is based on image analysis.

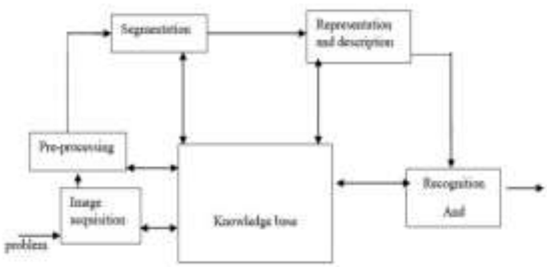
There are two types of methods used for image processing namely, analogue and digital image processing. Analogue image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers. The three general phases that all types of data have to undergo while using digital technique are pre-processing, enhancement, and display, information extraction.

• **Computer Vision :** Computer vision is a field of artificial intelligence that trains computers to interpret and understand the visual world. Using digital images from cameras and videos and deep learning models, machines can accurately identify and classify objects — and then react to what they "see."

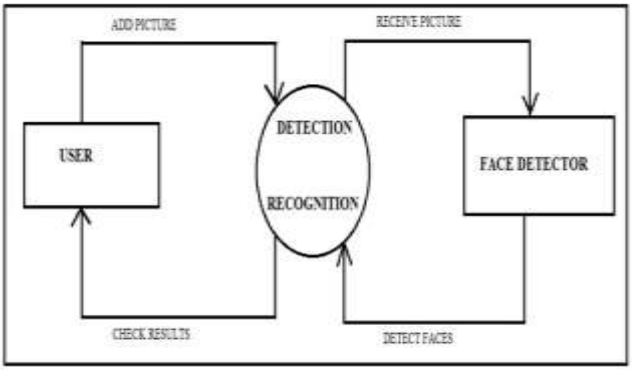
9.4 IV. SOFTWARE DESIGN □ UML DIAGRAMS

A UML diagram is a diagram with the purpose of visually representing a system along with its main actors, roles, actions, artifacts or classes, in order to better understand, alter, maintain, or document information about the system.

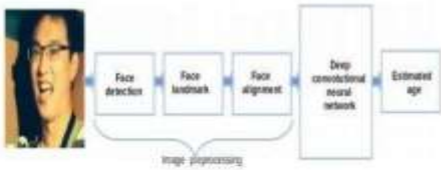
9.5 □ CLASS DIAGRAM

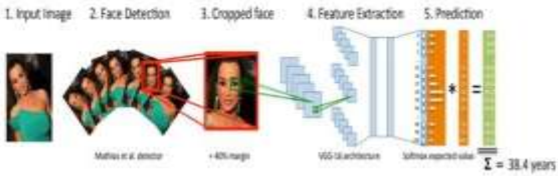


9.6 Fig. 1: Class Diagram

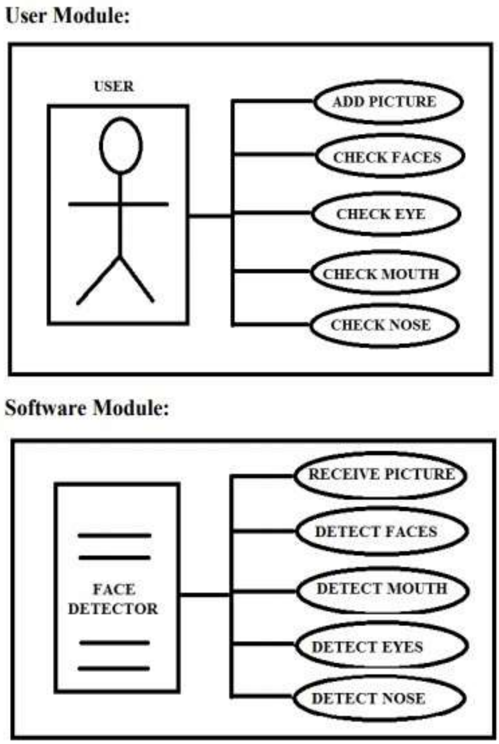


9.7 Fig. 2: Use Case Diagram





9.8 Fig. 3. Data Flow Diagram



9.9 Fig. 4. Design

The ideal approach is Age Prediction, since we expect an actual number as the output. However, it is difficult to estimate age with precise regression. And people can not determine age on the basis of a person's views precisely. Nonetheless, in their twenties or thirties we have an idea. It is therefore prudent to regard this topic as a classifying topic in which we seek to determine the age group in which the individual is present. For instance, in the 0-2 range is a single grade, 4-6 is a different grade etc.This must be borne in mind that estimating an age with a single image is not easy to solve as it depends on various variables, and in different parts of the world, the people of the same age will look very different.

In addition, before making predictions, we evaluated the use of face alignment and found that the predictions had improved for some cases but that they were worse for some people. When you mainly deal with non-frontal ears, it may be a smart idea to use alignment.

9.10 V. IMPLEMENTATION AND RESULT ANALYSIS HARDWARE REQUIREMENTS

- System : Intel i5 2.1 GHZ
- Memory : 4/8GB.
- Hard Disk : 1TB

9.11 SOFTWARE REQUIREMENTS

- Operating System : Windows 7/8 and above
- Domain : Machine Learning
- Scripts : Python
- Tool : Anaconda Navigator, Jupiter Notebook IDE
- Libraries : Numpy, pandas, math, cv2, matplotlib, seaborn, os, Image, scipy, sklearn, keras and tensorflow

9.12 DESCRIPTION OF LIBRARIES USED

NUMPY: NumPy is a library for the Python programming language, adding support for large, multidimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.

PANDAS: Pandas is a software library written for the Python programming language for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series.

MATPLOT LIBRARIES : Matplotlib is an amazing visualization library in Python for 2D plots of arrays. Matplotlib is a multi-platform data visualization library built on NumPy arrays and designed to work with the broader SciPy stack.

KERAS : Keras is an open-source neural-network library written in Python. It is capable of running on top of TensorFlow, R, Theano, or PlaidML. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible.

TENSORFLOW : TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks.

9.13 TOOLS USED

Anaconda Navigator : Anaconda is a free and open-source distribution of the Python and R programming languages for scientific computing (data science, machine learning applications, large-scale data processing, predictive analytics, etc.), that aims to simplify package management and deployment.

Jupyter Notebook IDE: Jupyter Notebook is an opensourced web-based application which allows you to create and share documents containing live code, equations, visualisations, and narrative text. The IDE also includes data cleaning and transformation, numerical simulation, statistical modelling, data visualisation, and many others.

Steps to follow:

1. Face detection with Haar cascade
2. Age Recognition with CNN

1. Face detection with Haar cascades:

This is a part most of us at least have heard of. OpenCV/JavaCV provide direct methods to import Haarcascades and use them to detect face

9.14 2. Age Recognition with CNN

CNN algorithm is used for age recognition. The CNN's output layer (probability layer) in this CNN consists of 5 values for 5 age classes ("1–14", "14–25", "25–40", "40– 60", "60-").

Procedure:

- First we are changing the current directory to the path where our image dataset is been stored by using os.chdir( ) and then we get the list of all the files and directories in the specified path using os.listdir( ).
- Shuffle( ) is used to randomize all the image files.
- Using split( ) we get the ids of image files and then store it in age variable.
- A list named classes is created to store ages less than 14 as 0, between 14 and 25 as 1,between 25 and 40 as 2, between 40 and 60 as 3 and above 60 as 4.
- Using misc.imread( ) and cv2.resize( ), we read an image from each file as an array and resize its dimensions to 32x32 and then store it in a list names X_data.
- Using squeeze( ), we remove single-dimensional entries from shape of array and store in the variable X.
- Next we normalize the data by converting the datatype of variable X to float32 and dividing it by 255.
- Slice the list classes up to 10 items and convert class vector(integers) to binary class matrix using to_categorical( ) before training our model.
- The total length of dataset is 23708, out of which 15008 is used for training, 1700 for testing and 7000 for validating the data.
- There are two ways to build keras models: sequential and functional. In our project we are using sequential by which we create a model layer-by-layer.
- When we use Conv2D as the first layer we must define input shape. This layer creates a convolution kernel that is convolved with the layer input to produce a tensor of outputs.
- MaxPooling2D layer is used for spatial data.
- Dropout layer is used to prevent a model from overfitting.

- Dense layer is a linear operation in which every input is connected to every output by a w eight.
- We summarize the model by using model.summary( ). Total params: 534,885, trainable params: 534,885 and Non-trainable params: 0
- Next we compile and fit the model.
- We then evaluate the model on test set to get the accuracy up to 0.6170588.
- Now the model is trained and its ready to predict the age of any random image from dataset.
- We plot a random sample of 10 test images, their predicted labels and ground truth.
- We get the output by displaying each image along with its title.

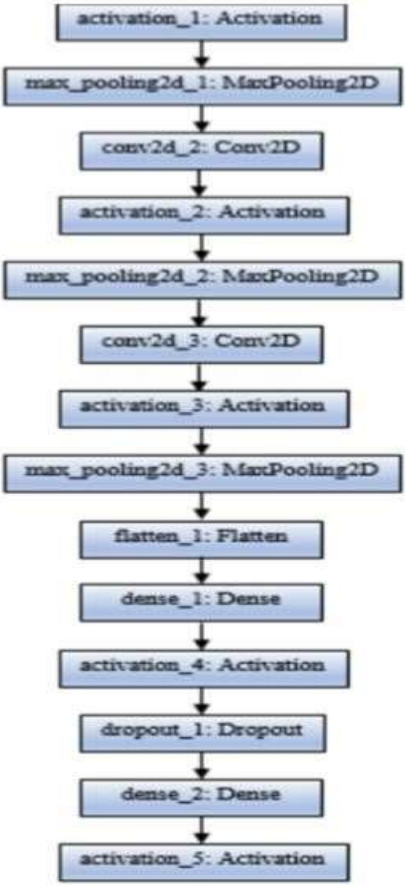
In this project, Keras is used to work on Tensorflow. Keras is an open-source neural network library. It is userfriendly and provides several features such as activation functions, layers, optimizers, etc. and it supports CNN . By using the appropriate class in Keras, deep learning models can be created on iOS and Android through the JVM (Java Virtual Machine). Keras enables the model to perform random transformations and normalization operations batches of image data by working on different attributes such as height shift, width shift, rotation range, rescale, range of shear, range of zoom, horizontal rip and fill mode. Using these attributes the system can automatically rotate, translate, rescale, and zoom into or out of images, as well as apply shearing transformations, rip images horizontally, fill in newly created pixels, etc. For the purpose of image classification, ConvNet is used.

Training Dataset: The training dataset is used as a set of examples used for training the model, i.e. to fit the different parameters.

Validation Dataset: A validation dataset is used to fit the hyper-parameters of the classifier. A validation dataset is necessary because it helps in the reduction of overfitting. The validation dataset is independent of the trainingdataset.

Test Dataset: The test dataset is used to test the performance of the classifier or model and to check the performance of characteristics such as accuracy, loss, sensitivity, etc. It is independent of the training and validation dataset.

9.15 MODEL FOR TRAINING THE DATA SET



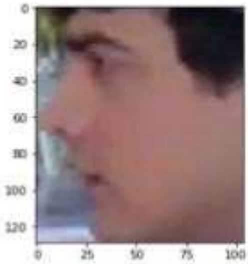
9.16 SYSTEM TESTING

System testingis a level of testing that validates the complete and fully integrated software product. The purpose of a system test is to evaluate the end-to-end system specifications. Usually, the software is only one element of a larger computer-based system. Ultimately, the software is interfaced with other software/hardware systems. System Testing is actually a series of different tests whose sole purpose is to exercise the full computer-based system.

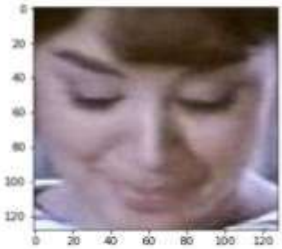
- The total length of dataset is 23708, out of which 15008 is used for training,1700 for testing and 7000 for validating the data.
- **Variations in shape**: One image had a shape (66, 46) whereas other had (102, 87).
- **Multiple viewpoints**: We have faces with whichever view possible.

- The system is tested based on all the possible angles of images and problems which may occur. The proposed system works quite well with all the testing conditions mentioned below with pretty well accuracy.

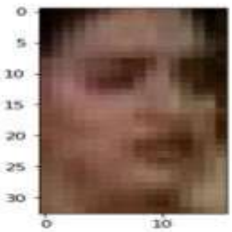
TEST CASE 1: side view



TEST CASE 2: front view



TEST CASE 3: Quality of images



9.17 VI. CONCLUSION AND FUTURE WORK

In this paper, we have used both image processing technique and machine learning algorithm for implementation and achieved a promising result for both Kaggle dataset and Nottingham Scan Database. As part of image processing, a pre-processing technique has been applied first. After pre-processing, feature extraction and classification are implemented in this system. A sigmoid function has been used as classifier in our model. Different optimizers have been used to determine which optimizer gives a better result. For assessing the effectiveness of our model, we have applied 5 fold cross-validation which has helped to evaluate our model. After analysing the result, a comparison of two previous work with our paper has also been shown where our system gives better result than them.

However, our system can be improved using different classifier for example softmax function and ReLU. A more efficient system can be built for human gender classification using Belief Rule Based Expert Systems (BRBES) [15–18, 25,31]. So in future, we will implement all these for human gender classification.

The model proposed was developed very carefully and error-free while being efficient. During this research, we proposed a model to estimate people's age by feeding the CNN image dataset, a deep learning algorithm and trained in broad database face-recognition. In all, we think that the accuracy of the model is decent and better than many already existing model, but can be further improved by using more data , data increase and better network architecture. The project model also predicts the age of the image provided with little slip and angle issue.The completely automated face recognition program was not sufficiently reliable to achieve high accuracy of recognition. It was mainly due to the fact that even a slight invariance to the size, rotation or shift errors of the segmented facial image did not occur in the face recognizing subsystem.

This project allows us to obtain useful knowledge about a variety of topics such as deep learning, the use of different libraries such as Keras, Pil, Seaborn, Tensorflow. The entire model is protected and this project has also enabled us to understand the stages of a project's creation and the working together. We have also learned how to test various project features.This project has given us great pleasure in creating a concept that can be used for good purposes and health in real life. In our project, there is ample scope for further development. For addition, a variety of features such as gender and age can be applied to this program. Outside of classification for age prediction, a regression model may also be used, if enough data is available. Through developing this project further, camera footage for safety purposes can be used for real-time age prediction.Nevertheless, if a more processing such as an eye detection technology has been applied to further normalize the segmented facial image, the output will expand to levels comparable to the manual facial detection and recognition system. This is one of the system needs identified in this section. Good techniques such as iris or retina recognition and facial recognition are used for user access and user authentication applications using the thermal range as this requires very high precision. The automatic real time system will be perfect for crowd control application.

Invariant face detection and recognition systems.In order to be used in simple surveillance applications, such as ATM user security, the fully automated face detection and recognition System (with an eyeshoot detection system) could be applied, whereas manual face detection and an automated recognition system is ideal for the mug shot matching. Implementation of a technique for eye detection would be a small extension to the system implemented and require little additional investigation. All other methods have shown good results and rely on the deformable prototype and main component analysis strategies.

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