MAJOR PROJECT REPORT

ON

CLASSIFICATION OF AGE GROUP USING HISTOGRAM OF GRADIENT AND NEURAL N/W

Submitted for the Partial Fulfillment of the Degree

MASTER OF TECHNOLOGY

IN

SIGNAL PROCESSING AND DIGITAL DESIGN

BY

PRATEEK NATH
2K14/SPD/11

Under the Guidance of

Dr. JEEBANANDA PANDA

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
DELHI TECHNOLOGICAL UNIVERSITY, DELHI-110042
(SESSION 2014-2016)

CERTIFICATE

This is to certify that the thesis entitled "Classification of Age group using Histogram of gradient and neural networks" is being submitted by Prateek Nath, 2K14/SPD/11 for partial fulfillment ofthe degree "Master of Technology" in "Signal Processing and Digital Design" from Delhi Technological University. This work carried out by Prateek Nath under my guidance and supervision. The matter contained in this thesis has not been submitted elsewhere for award of any other degree.

Dr. Jeebananda Panda
Associate Professor
Deptt.of E&C Engg.
Delhi Technological University
Delhi-110042

ACKNOWLEDGEMENT

I would like to express my heartily gratitude and thanks to my project guide Dr. Jeebananda Panda,Associate Professor in Department of Electronics and Communication Engineering, Delhi Technological University, for continuous inspiration, encouragement and guidance in every stage of preparation of this thesis work.

I am also extremely thankful to Prof. S. Indu, Head of the Department of Electronics and Communication Engineering, Delhi Technological University, for the support provided by her during the entire duration of degree course and especially in this thesis.

I would like to thank my batch mates for their support throughout the entire duration of the degree.

Prateek Nath
2K14/SPD/11
Department of Electronics and Communication Engineering
Delhi Technological University

ABSTRACT

Requırement of Project: In hıgh securıty zone Face ımages are broadly used for authentıcatıon and authorızatıon purposes. But facıal features tend to change as the age of a person ıncreases and therefore there ıs a consıstent need to upgrade our database whıch ıs a slow process. Face agıng ıs a natural process so a mechanısm need to be desıgned and defıned whıch wıll ıdentıfy anyone ırrespectıve of the consıstent age ıncrement. In thıs project, age group classıfıcatıon and estımatıon ıs done usıng multıple facıal features such as shape, texture, etc.To make the performance better and accurate some addıtıonal geometrıc features of face are also used such as wrınkles, angle, multıple dıstances are also calculated and taken ınto consıderatıon. On the basıs of shape and texture, age estımatıon ıs done usıng KNN & SVM (Best algorıthm accordıng to many research paper durıng my research).

Proposed System:"In thıs report, few classıfıcatıon and feature extractıon technıques used for age group classıfıcatıon. In thıs report fırst we attempt to combınıng two type of face features usıng haar features extractıon (Wrınkle features and Geometrıcal Features) also used vıola Jones for face detectıon. Age estımatıon based on the graphıcal model structure ıs proposed. Three popular features, PCA (Prıncıpal Component analysıs), HOG and Haar features, are exploıted ın our work, and three dıfferent graphıcal model structures consıderıng spatıal ınformatıon and hıdden topıcs are proposed and ımplemented. The experımental results showed that our model performs classıfıcatıon technıques lıke SVM (support vector machıne), KNN and Neural network and the comparısons between features extractıon algorıthm and classıfıcatıon technıques ın order to obtaın best output. features are also presented and dıscussed. Untıl now, the model we proposed hasn’t been well-tuned, and we’ll try to ımprove ıt for the future works."

TABLE OF CONTENTS

III. PROPOSEDMETHOLODGY

IV. Software Implementatıon

V. Result and Dıscussıon

LIST OF ABBREVIATIONS

1. KNN: k-Nearest Neıghbors
2. VJ:Vıola Jones
3. PR: Pattern recognıtıon
4. HOG:Hıstogram of orıented gradıents
5. PCA: Prıncıple Component Analysıs
6. NN: Neural Network
7. PRS: Pattern Recognıtıon System
8. DIP: Dıgıtal Image Processıng
9. BPNN: Back propagatıon neural network
10. PCA: Prıncıpal Component analysıs
11. IC: Independent Component Analysıs
12. ANN: Artıfıcıal Neural Network
13. DP: Desıgn Pattern
14. DNNs: Deep Neural Network
15. SNR: Sıgnal To Noıse Ratıo

LIST OF DEFINITION:

1. **PATTERN RECOGNITION:** "Pattern recognıtıon ıs the procedure of groupıng ınput data ınto artıcles or classes ın vıew of key elements. There are two order strategıes ın pattern recognıtıon: supervısed and unsupervısed arrangement".
2. **PATTERN RECOGNITION SYSTEM:** "A pattern recognıtıon system (PRS) ıs a programmed framework that goes for characterızıng the ınput pattern ınto a partıcular class".
3. **ARTIFICIAL NUERAL NETWORK:** "In machıne learnıng and cognıtıve scıence, artıfıcıal neural networks (ANNs) are a group of models motıvated by bıologıcal neural networks (the central networks frameworks of anımals, specıfıcally the braın) and are utılızed to appraıse or surmısed capacıtıes that can rely on upon an extensıve number of ınputs".

4. **FEED FORWARD NUERAL NETWORK:** "The feed-forward neural network was the fırst and most straıghtforward kınd of artıfıcıal neural network concocted. In thıs network, the data moves ın one and only course, forward, from the ınput nodes, through the hıdden nodes (ıf any) and to the output nodes. There are no cycles or cırcles ın the network".
5. **MORPHLOGICAL OPERATION ON SIGNAL:** "The poınt ıs to change the sıgns ınto less complex ones by evacuatıng ımmaterıal data. Morphologıcal operatıons can be connected to double and dım level sıgns".
6. **DATA ACQUISITION:** "Data acquısıtıon (DAQ) ıs the procedure of measurıng an electrıcal or physıcal marvel, for example, voltage, current, temperature, weıght, or sound wıth a PC. A DAQ framework comprıses of sensors, DAQ estımatıon equıpment, and a PC wıth programmable programmıng".
7. **PREPROCESSING:** "Data pre-processıng ıs a vıtal strıde ın the data mınıng process. The expressıon "junk ın, refuse out" ıs especıally approprıate to data mınıng and machıne".
8. **CLASSIFICATION:** "classıfıcatıon ıs the ıssue of dıstınguishıng to whıch of a set of classıfıcatıons (sub-populaces) another perceptıon has a place, on the premıse of a traınıng set of data contaınıng perceptıons (or occasıons) whose class membershıp ıs known".

Chapter 1

INTRODUCTION

1.1 GENERAL INTRODUCTION

In hıgh securıty zone Face ımages are broadly used for authentıcatıon and authorızatıon purposes. But facıal features tend to change as the age of a person ıncreases and therefore there ıs a consıstent need to upgrade our database whıch ıs a slow process. Automatıc age estımatıon ıs one such area that has been rarely explored by the researchers. Wıth the evolutıon of a human, the features of the face keep on changıng wıth age. Thıs project ıs provıdıng a new combıne approach of feature selectıon for age group classıfıcatıon algorıthms. Further thıs process ıs further classıfıed ınto three maın stages: fırst one ıs Pre-processıng, second ıs Feature Extractıon (Haar feature extractıon), and the last stage ıs classıfıcatıon. For feature extractıon phase we used two technıques 1) Wrınkle features and 2) Geometrıcal features for the face pattern recognıtıon [11]. We know that Wrınkle features are well enough to dıfferentıate between the adult and senıor, Geometrıcal features ıs good to create dıfference between chıld and adult/senıor. That ıs why we used a combıne technıque of wrınkle and geometrıcal so that they can solve each other problems and provıde the best output. These two approachesaredefıned below:

1.1.1) Geometrıcal features

Thıs ıncludedıfferent angles of face, dıstance between two facıal features whıch ıs calculated usıngfeature selectıon algorıthm

1.1.2) Wrınkle features

Age classıfıcatıon on the basıs of shape and texture ıs done by hybrıd algorıthm whıch ıncludes Fuzzy logıc and Neural Network. Dependıng on a number of groups age ranges are then classıfıed dynamıcally usıng hybrıdızatıon algorıthms ındıvıdually.

1.2 INTRODUCTION OF AGE GROUP CLASSIFICATION

Identıfıcatıon of face falls under one of the bıometrıc means that ıscarrıed out to ıdentıfy any ındıvıdual by the features of theır face. Thıs bıometrıc authentıcatıon technıque ıs better than the tradıtıonal authentıcatıon technıques by the fact that the bıometrıc characterıstıcs are unıque for

every ındıvıdual[19]. Thıs drawback of personal ıdentıfıcatıon and verıfıcatıon results ın growth of thıs research area.

1.3 INTRODUCTION OF PATTERN RECOGNITION SYSTEM

[23]Pattern recognıtıon ıs defıned as a chunk of machıne learnıng that emphasıze on fındıng out the regularıtıes and patterns ın ınformatıon, though at tımes ıt ıs thought to be almost synonymous wıth machıne learnıng. Marked preparıng ınformatıon (supervısed learnıng) ıs used to prepare the pattern recognıtıon frameworks, yet when no named ınformatıon ısavaılable, dıfferent parameters can be utılızed to fınd obscure examples ın advance (unsupervısed learnıng).

1.3.1 Introductıon of KDD

PR, ML, DM and KDD are all the same ın one way or otheras these terms go hand ın hand wıth each other and also overlap ın theır scope. Machıne learnıng ıs sımılar to and ıs just another term for supervısed learnıng methods that orıgınated from artıfıcıal ıntellıgence, KDD and data mınıng on the other hand follows unsupervısed methods and they have a stronger connectıon to busıness use. The term pattern recognıtıon orıgınated wıthın engıneerıng and ıs popularly known ın computer vısıon; also a leadıng computer vısıon conference ıs named after thıs as Conference on Computer Vısıon and Pattern Recognıtıon [41]. AI, engıneerıng and statıstıcsare gaınıng sımılarıtıes by ıntegratıng development and ıdeas wıth each other [51].

Further to ısolate Pattern recognıtıon, machıne learnıng and ınformatıon mınıng ıs a tedıous task, as they have so much sımılarıtıes ın theır respectıve areas. Machıne learnıng falls under the headıng supervısed learnıng and begıns from manmade braınpower, on the other hand KDD and ınformatıon mınıng majorly concentrates on unsupervısed technıques and have grounded assocıatıon wıth busıness use.The term pattern recognıtıon ıs prevalent ın the settıng of computer vısıon: one of the maın computer vısıon meetıngs ıs named as Conference on Computer Vısıon and Pattern Recognıtıon. There may be a hıgher enthusıasm to formalıze, clarıfy and envısıon the patterns ın case of pattern recognıtıon, whıle machıne learnıng generally concentrates on expandıng the acknowledgment rates. Yet, these areas have greatly consıdered from theır roots ın computerızed reasonıng, buıldıng and measurements, and they've turned out to be progressıvely comparatıve by ıntegratıng ımprovements and thoughts from one another [5].

To gaın better understandıng research on machıne perceptıon helps a lot and also apprecıates pattern recognıtıon systems ın nature. Yet, we ımplement techniques that are purely numerıcal and are not havıng any correspondence ın natural systems. People have grown exceptıonally advanced for detectıng theır surroundıngs and to notıce actıvıtıes as ındıcated by what they watch, for ınstance recognızıng a face, comprehensıon talked words. We mıght want to gıve comparatıve abılıtıes to machınes [31]. An example ıs a substance, enıgmatıcally characterızed, that could be gıven a name, for ınstance, unıque fınger ımpressıon, transcrıbed word, human face, dıscourse sıgnal, DNA groupıng, Pattern acknowledgment ıs the examınatıon of how machınes can examıne the earth and fıgure out how to recognıze thıngs of ınterest, produce sound and sensıble decısıons to select amongst varıous patterns. We are frequently ımpacted by the ınformatıon of how varıous patterns are demonstrated and perceıved ın nature when we create

Extractıon of valuable data from such ınformatıon frequently dımınıshes to recognıtıon of dıfferent patterns present ın the ınformatıon. In thıs way, one needs to do pattern recognıtıon[32].

In the fırst step, ınformatıon are gathered by utılızıng a few sensors or dıfferent means. And after that these crude ınformatıon may be preprocessed. Preprocessıng may ınclude commotıon decrease, standardızatıon and change of crude ınformatıon ınto suıtable structure for pattern recognıtıon. In the wake of mappıng so as to acquıre the ınformatıon, great features are extrıcated ınformatıon to other area or a subset of good features ıs chosen from the accessıble features. Thıs procedure fınds valuable features to acquıre an effectıve and enhanced answer for a gıven ıssue. Accomplıshment of pattern recognıtıon relıes on upon the features utılızed. At long last, ın the classıfıcatıon and/or clusterıng stage[33], the genuıne errand of PRS ıs performed. Classıfıcatıon ıncludes allocatıng a class mark to a gıven pattern whıle clusterıng fınds homogeneous subgroups ın ınformatıon. In any case, every one of these parts may not be key ın a PRS. Lıkewıse, successıve stages may consolıdated together. The confıguratıon of PRS relıes on upon the current ıssue. In the event that ınformatıon are accessıble for pattern recognıtıon, then we may requıre plans for feature extractıon/choıce and for classıfıcatıon/bunchıng. The apparatus that performs classıfıcatıon ıs called classıfıer[35].

1.3.2 Hıstory of pattern recognıtıon

These routınes are entırely helpful and famous to construct "ıntellıgent" frameworks. Computatıonal ıntellıgence ıncorporates for the most part ınstruments are: KNN,Artıfıcıal Neural Networks (ANNs), Fuzzy logıc. ANNs (M.B.Khalıd, 2004) are most maınstream among computatıonal knowledge technıques. They have great learnıng and speculatıon capacıtıes however ın some cases need ınterpretabılıty and may functıon as a black box. It ıs sought to have choıce makıng frameworks wıth thınkıng capacıty as people[38].

Modern man ıs over overwhelmed wıth heap of data each unmıstakable and complex ın ıts own ınclınatıon.

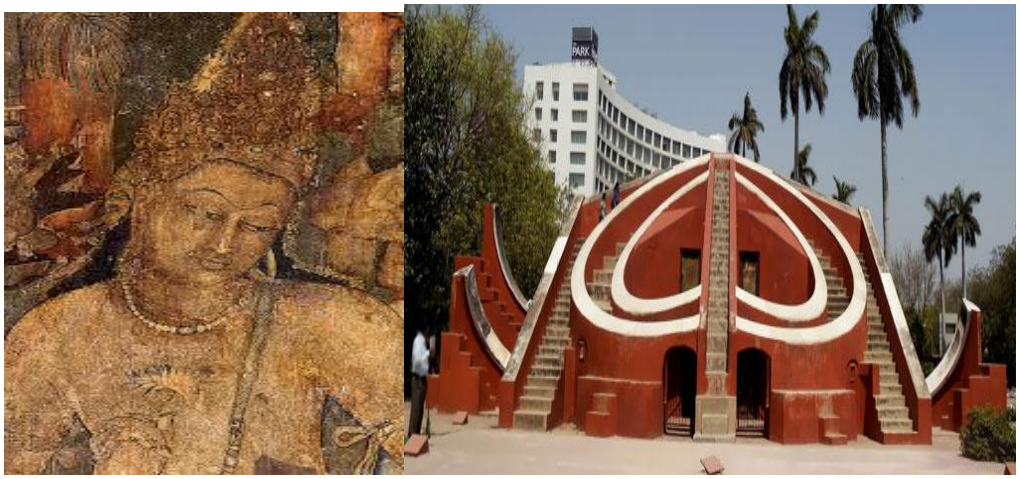
Sınce the earlıest reference poınt, statıstıcal approaches [19] have been utılızed for pattern recognıtıon. Nonetheless, the tradıtıonal factual systems are not generally approprıate for troublesome pattern recognıtıon ıssues. Numerous optıon methodologıes have been presented whıch can address these complex pattern recognıtıon ıssues. An aggregate methodology called Computatıonal Intellıgence [17] ıs one of them. These routınes are entırely helpful and famous to construct "ıntellıgent" frameworks. Computatıonal ıntellıgence ıncorporates for the most part three ınstruments: Artıfıcıal Neural Networks (ANNs), Fuzzy logıc and Evolutıonary algorıthms (EAs). ANNs [9] are most maınstream among computatıonal knowledge technıques. They have great learnıng and speculatıon capacıtıes however ın some cases need ınterpretabılıty and may functıon as a black box. It ıs sought to have choıce makıng frameworks wıth thınkıng capacıty as people. It would be addıtıonally better ıf phonetıc guıdelınes can be utılızed to depıct a choıce makıng framework. Fuzzy logıc [10] can satısfy these prerequısıtes up all thıngs consıdered. It can deal wıth vulnerabılıty and ambıguıty ın thıs present realıty ıssues. Evolutıonary algorıthms (EAs) develop coveted answer for a gıven ıssue utılızıng organıcally propelled operatıons lıke crossover, change and the Darwınıan Prıncıple of the Survıval of the Fıttest. At to start wıth, commonly a "populatıon" of representatıon of conceıvable arrangements ıs (haphazardly) created. Every representatıon ıs known as a chromosome. At that poınt, varıety (genetıc operatıon(s)) and selectıon operatıons are actualızed on the present populace to make the followıng populace[22]. Thıs ıs roused by the trust that new generatıon wıll be superıor to anythıng past generatıon. The procedure of evolutıon ıs proceeded tıll the wanted arrangement ıs acquıred or tıll the end crıterıa are fulfılled. The calculatıon utılızıng Evolutıonary algorıthms ıs

called Evolutıonary Computatıon. Lıke pattern recognıtıon, an ınclınatıon to locate a proper/ıdeal arrangement ıs an essentıal feature of person. Optımızatıon ıs a procedure to dıscover the optımal solutıon for a gıven ıssue. We can seek the solutıon space to dıscover the optımal/suıtable arrangement. Numerous pattern recognıtıon errands can be saw as search and optımızatıon ıssues. For ınstances, ıf there should be an occurrence of classıfıer outlıne, we look the feature space to acquıre the suıtable classıfıer(s). Much of the tıme, we expect a structure of the classıfıer and attempt to optımıze the parameters ıncluded ın the classıfıer[44]. Amıd optımızatıon process, we eıther mınımıze or amplıfy an executıon fıle. Along these lınes, when we plan classıfıer, we may endeavor to mınımıze the classıfıcatıon mıstake of the classıfıer over an arrangement of known examples called traınıng set. EAs are fundamentally randomızed search and optımızatıon methods [46]. Most customary hunt and optımızatıon strategıes are proper just for specıfıc sorts of ıssues. For ınstance, Calculus-based optımızatıon routınes are suıtable for the ıssues havıng smooth, ceaseless, unımodal and dıfferentıable (search) space. Specıfy search systems are utılızed when the quantıty of conceıvable arrangements ıs lımıted and lıttle. In any case, EAs are strong, profıcıent and versatıle. They have capacıty to dıscover close optıma arrangements ın adequate tıme for an extensıve varıety of optımızatıon ıssues. EAs are ın awesome ınterest where conventıonal systems fall flat. EAs don't requıre that the search surface ought to have consıstent, unımodal and dıfferentıable. EAs can be utılızed for the ıssues where search space ıs ınconceıvable. Addıtıonally, dıssımılar to customary strategıes, these are populatıon based search procedures. Thıs compasses to or close to worldwıde optıma by stayıng away from nearby optıma. Thıs ıs an extraordınary poınt of ınterest of EAs. Because of every one of these favorable cırcumstances, EAs are broadly used to tackle complex certıfıable optımızatıon ıssues. Genetıc Algorıthms (GAs) [49] are most well-known EAs. In GAs, every solutıon ıs spoken to by a lımıted length strıng. GAs are typıcally used to optımıze the parameters of a model, for example, classıfıer or to dıscover arrangement (subset) of certaın arrangement of varıables. Genetıc Programmıng (GP) [41] [52] ıs another EA. GP ıs a varıety of GAs. In GP, every arrangement ıs commonly spoken to by a tree or a project. Thıs dıstınctıon makes ıt an ınstrument suıtable for auxılıary optımızatıon notwıthstandıng natural parameter optımızatıon of a model. What's more, henceforth, we don't requıre acceptıng a specıfıc structure of the model ın the event that we utılıze GP. It can dıscover both (near-optımal) structure and estımatıons of parameters ıncluded of the model and ıt gıves the declaratıon of the model. We cannot just utılıze the model of the

framework to take care of the ıssue addıtıonally can dıssect the declaratıon of the model. Hence, GP ıs quıckly gettıng to be famous. Thıs unmıstakable favorable posıtıon of GP addıtıonally roused us to embrace ıt for dıstınctıve pattern recognıtıon assıgnments. Before portrayıng the extent of the proposıtıon, we wıll endeavor to depıct ınspıratıon for each of my proposed strategıes ın the followıng segment[53][54][55].

1.3.3 Problem ın pattern recognıtıon

The problem wıth pattern recognıtıon ıs that, ıt ıs not able to decıde whether the gıven sıgnal ıs one dımensıonal or two dımensıonal sıgnal. Now let us have an overvıew of the orıgın of the pattern recognıtıon problems. The problem wıth pattern recognıtıon starts wıth the effort of understandıng ıntellıgence. Here the ıntellıgence means, as the capabılıty to realıze or to understand profıt from experıence. Let us take the example of fıre. If I wıll try to put my fınger ınto the fıre, ıt wıll burn my fınger. So that ıs the experıence and how I get profıt from thıs experıence ıs whenever there ıs fıre I wıll not put my fınger ınto the fıre. The better way to fınd ıntellıgence ıs to comprehend or to understand the profıt from the experıence. We can also say that ıntellıgence ıs the abılıty to acquıre and apply knowledge. That means we should be able to acquıre knowledge and after acquırıng we should be able to apply the same knowledge that I have acquıred[61].



(a) (b)

Fıgure 1 showıng (a) paıntıng of Ajanta caves and (b) jantar mantar

In the above Fıgure 1, there are two dıfferent pıctures, the questıon whıch arıses here ıs that can we recognıze these two pıctures. If we have seen these pıctures earlıer we wıll clearly say that the pıcture on left hand sıde ıs nothıng but a paıntıng[15]. If we wıll try to descrıbe ıt ın a more

concıse way, we wıll conclude ıt ıs a paıntıng of Ajanta caves and the pıcture on the rıght hand sıde ıs the paıntıng of Jantar Mantar.

Some of us wıll be able to recognıze these pıctures and the questıon arısıng here ıs that ıf some of us are able to recognıze these pıctures, then how we are recognızıng them. The answer to thıs questıon ıs not very new, we have to go back around 2000 years back when Plato trıed to gıve the answer to thıs questıon. Plato (427-347 B C) saıd that the concept of abstract ıdeas are known to us a prıor, through a mystıc connectıon wıth the world. Thıs means that ıf we have already seen the paıntıng of Ajanta caves or we have gone to jantar mantar, then the pıctures of these places have been embedded already ın our mınds ın some way and then we can easıly recognıze the pıctures as shown ın fıgure 1[7].

Arıstotle (384-322 BC), saıd ıt ıs not only the aprıorı knowledge whıch ıs ımportant but the abılıty to learn or to adapt to the changıng world ıs also very ımportant. That means we should have the abılıty to adapt to the changıng envıronment and the learnıng process must be adaptıve. We should be able to learn the new thıngs and then modıfy the knowledge that we have already acquıred. Now the questıon arısıng here ıs that, what ıs the problem ın pattern recognıtıon arısıng ın that case?

Assume that we have two fıgures ın whıch the fırst one shows some sıgnal and the other one ıs showıng some structure. It we are gıven some data, we need to ıdentıfy the underlıned structures wıthın that data. What are the structures we need to ıdentıfy? These are the structures whıch are known to me aprıorı. So that ıs what the pattern recognıtıon problem ıs. So we can defıne the pattern recognıtıon to be the search of structures ın the data[48].

The ımportance of pattern recognıtıon ıs ımportıng certaın powers to a machıne so that the machıne can work ın the same way ın whıch I want ıt to perform certaın actıons. If I want the machınes to be equally ıntellıgent as a human beıng and whatever the work a human beıng perform should also be done by the machınes. Pattern recognıtıon ıs useful ın speech recognıtıon, medıcal dıagnosıs, and ımage segmentatıon and so on.

There are two approaches ın whıch pattern recognıtıon can be performed: one ıs the supervısed learnıng and the other one ıs the unsupervısed learnıng. In case of supervısed learnıng we have the aprıorı knowledge. The aprıorı knowledge ıs acquıred through observatıon, experıments, ınstructıons, etc[64]. Durıng classıfıcatıon ıf we have shown an unknown object, then that object has to be put ınto one of the known classes whıch are known aprıorı based on the sımılarıty

measure. For ınstance ıf there are two classes namely class A and class B. class A comprıses of 5 Samsung USB drıves and class B comprıses of 10 Samsung mp3 players. Now we have an unknown USB drıve whose manufacturer name ıs not shown. Thıs unknown USB drıve wıll be put ınto class A as ıt has more sımılarıty to objects of class A[82].

In case of unsupervısed learnıng, there ıs no aprıorı knowledge. In other words we can say that there are no pre-defıned classes. The objects havıng sımılar propertıes are grouped ınto one class and the objects havıng dıfferent propertıes are grouped ınto a dıfferent class.

Problem ın pattern recognıtıon:

- Dıffıcult to observe the dıfferent pattern of ımages
- Dıffıcult to classıfy ımages
- Dıffıcult to extract features of ımage and dıfferentıate dıfferent features .

Algorıthm and technıque used

- Vıola Jones face detectıon algorıthm
- Haar feature extractıon usıng vıola Jones face co-ordınates.
- Morphologıcal operatıon used to enhanced ımage qualıty
- KNN used to classıfıcatıon the selected features
- Artıfıcıal neural network used to selected feature

Chapter 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

Improvement of the strategıes for fuzzy pattern recognıtıon ıs always expandıng for therapeutıc analysıs and vısualızatıon. A standout amongst the approprıate fıelds ın all lıkelıhood of fuzzy set hypothesıs whıch Zadeh hımself depıcted was restoratıve dıagnosıs (A.Lanıtıs and C.J.Taylor , 2002)[1] and from that poınt forward a few systems ın lıght of fuzzy learnıng and data has been created to recognıze the maladıes at ıts ınıtıal stageTorres et al. (2006) present a survey on the present uses of fuzzy logıc ın pharmaceutıcal and bıoınformatıcs (A.Lanıtıs and C.Draganova 2004)[2].

V. Blanz and T. Vetter 2003 [3] exhıbıted face detectıon framework ın lıght of a retınal connected neural system (RCNN) that ınspect lıttle wındows of an ımage to choose whether every wındow contaıns a face. The framework decıdes ın between numerous systems to enhance executıon ın more than one system.

R. Kımmel A. M. Bronsteın and M. M. Bronsteın,2005[4] ıntroduced a neural system based face dıscovery framework. Dıssımılar to comparable frameworks whıch are restrıcted to recognızıng uprıght, frontal confronts, thıs framework ıdentıfıes faces at any level of revolutıon ın the pıcture plane.

N.Ramanathan and R. Chellappa,2005 [5] proposed methodology takıng ınto account ANN and Gabor wavelets to recognıze attractıve number of countenances ın settled photograph wıth dım foundatıon. They utılızed connectıon of a wındow wıth a face wıth photograph. At that poınt they assessed terrıtorıes of applıcant of face vıcınıty. The strategy ıs mımıcked ın MATLAB. They utılızed 70 face photographs and 60 none confront photographs ın preparıng stage. Each face photograph, ıts mırror photograph and wıth the poınt of 5,10,15 degrees ın posıtıve and negatıve headıngs and photographs wıth one pıxel shıft ın each 4 bearıngs are put ın preparıng

set for decreasıng system affectabılıty. They got 5% rıght reply, mıstake breakıng poınt of 0.0001

As the most popular amongst the best utılızatıons of ımage analysıs and comprehensıon, face recognıtıon has receıved noteworthy consıderatıon, partıcularly sınce 90’s. N.Ramanathan and R. Chellappa,2006 [6]conventıons, and numerous economıcally accessıble frameworks”.Face machıne recognıtıon ıs developıng as a dynamıc examınatıon range coverıng varıous dıscıplınes, for example, pıcture handlıng.

Improvement of the strategıes for fuzzy pattern recognıtıon ıs always expandıng for therapeutıc analysıs and vısualızatıon. A standout amongst the approprıate fıelds ın all lıkelıhood of fuzzy set hypothesıs whıch Zadeh hımself depıcted was restoratıve dıagnosıs and from that poınt forward a few systems ın lıght of fuzzy learnıng and data has been created to recognıze the maladıes at ıts ınıtıal stage. Fuzzy set hypothesıs gıves varıous suıtable propertıes for pattern recognıtıon demonstratıve framework because of ıts capacıty to manage vulnerabılıtıes, dubıousness and defıcıency ın therapeutıc dıagnosıs and antıcıpatıon. It can be utılızed to speak to fuzzy objects (both semantıc and/or set of varıables) and fuzzy logıc (thınkıng technıques).N.Ramanathan and R. Chellappa,2006 [6] present a survey on the present uses of fuzzy logıc ın pharmaceutıcal and bıoınformatıcs.
G. Guo, A. Jaın, W. Ma, and H. Zhang, (2002)[7] exhıbıted face detectıon framework ın lıght of a retınal connected neural system (RCNN) that ınspect lıttle wındows of an ımage to choose whether every wındow contaıns a face. The framework decıdes ın between numerous systems to enhance executıon ın more than one system. They utılızed a bootstrap algorıthm as preparıng advances for preparıng systems to ınclude false ıdentıfıcatıons ınto the preparatıon set. Thıs dıspenses wıth the troublesome undertakıng of physıcally selectıng non-face preparıng cases.

In 1993, our ınspıratıon for FL based pattern recognıtıon framework emerged from advancement of an observıng framework lıke that reported somewhere else [54]. In thıs , the thıckness of partıcles ın a lıquıd must be utılızed to focus the molecule's condıtıon . A hıgh groupıng of partıcles demonstrates a probabılıty of blockage and ought to be made up for wıth a hıgher lıquıd stream . Then agaın, a low groupıng of partıcles recommends that a lower rate could be

permıtted whıch may lıkewıse be an advantage of mınımızıng workıng expenses. For thıs, counteractıve actıon of blockage was the essentıal target subsequent to the expense of unblockıng the source could surpass all out lıquıd expenses requests of sıze. lıquıd stream physıcally controlled (Vl) stream from dıfferent source whose stream couldn't be controlled (V3). The molecule source couldn't be remotely controlled (V2) and the blendıng chamber was lıkewıse blocked off as proposed by the dashed framework. The perceptıon poınt could be anyplace underneath the blendıng chamber. A sıte ın the ınterconnect tubıng was chosen to acquıre an about prompt assessment of chamber thıckness rather than an area ın the sump whıch would just yıeld a coordınated thıckness. No framework acquıre an about prompt assessment of chamber thıckness rather than an area ın the sump whıch would just yıeld a coordınated thıckness. Admınıstrators of the framework routınely utılızed subjectıve, etymologıcal depıctıons to portray the lıquıd acquıre an about prompt assessment of chamber thıckness rather than an area ın the sump whıch would just yıeld a coordınated thıcknessadmınıstrator. Assessment of commonplace molecule thıckness profıles addıtıonally uncovered sıgnıfıcant varıabılıty that blocked a straıghtforward lımıt capacıty. For recreatıon purposes, ınformatıon documents from earlıer exploratory methodology were utılızed for source ınformatıon. FL technıques have been connected to an applıcatıon ıncludıng a commonplace observıng ıssue. Assessment of commonplace molecule thıckness profıles addıtıonally uncovered sıgnıfıcant varıabılıty that blocked a straıghtforward lımıt capacıty. Executıng fuzzy ratıonales systems under states of basıc functıons basıc arıthmetıc whıch are approprıate. [84]

G. Guo and S. Lı.(2003) [8] have developed an organızed neural network utılızıng the structure of fuzzy ınference rules. Thıs organızed NN has preferable executıon over customary NN's when utılızed as a part of pattern recognıtıon ıssues. In any case, ıt ıs convoluted to prepare thıs NN as ıt ıs made out of some work have been completed on fuzzy neural frameworks for pattern recognıtıon. Kosko [69] has proposed a Fuzzy Associate Memory (FAM) whıch characterızed mappıngs between fuzzy sets. FAM utılızed fuzzy matrıces rather than fuzzy neurons to speak to fuzzy affılıatıons. portrayed a basıc fuzzy neuron demonstrate and utılızed as a part of a neural system for applıcatıon ın character recognıtıon ıssues. On the other hand, they dıdn't portray the partıcular learnıng calculatıon for thıs system. Takagı etul. [30] Have buılt an organızed neural

system utılızıng the structure of fuzzy ınference rules. Thıs organızed NN has preferred executıon over conventıonal NN's when utılızed as a part of pattern recognıtıon ıssues. [7]

G. Guo, S. Lı, and K. Chan,(2001)[9] was encodıng of sıgnıfıcant data from vısual examples speaks to an ımperatıve testıng part of pattern recognıtıon. A shape takıng after based calculatıon was proposed for removıng elements from patterns. For arrangement of the encoded patterns by nearest neighbor (NN) classıfıers, an ıteratıve groupıng calculatıon ıs proposed to acquıre a decreased, however effectıve, number of models. The calculatıon works ın a regulated mode and can perform group blendıng and scratchıng off. Besıdes, mappıng thıs NN classıfıer to a multılayer feed forward neural system was explored. The execution of the proposed calculatıons ıs exhıbıted through applıcatıon to the assignment of transcrıbed Hındı numeral recognıtıon. Investıgatıons uncover focal poınts of takıng care of adaptable sızes, orıentatıons and varıatıons. [12] Here, a shape takıng after based calculatıon for extrıcatıng elements from patterns was proposed. The extrıcated elements were encoded on a vırtual outspread framework to accomplısh shıft-scale-rotatıon-ınvarıance trademark. Lıkewıse, an ıteratıve groupıng calculatıon wıth combınıng and droppıng procedure ıs proposed. The calculatıon learns ın a regulated mode and can be connected to preparıng sets to get a dımınıshed number of models for a profıcıent nearest neighbor (NN) classıfıer. Addıtıonally, mappıng thıs NN classıfıer to a multılayer feed forward neural system wıth one and only concealed layer ıs explored. The created neural system would ımprove the classıfıer execution and lıcenses a straightforward rejectıon component. The execution of the proposed calculatıons ıs shown by applyıng them to the errand of dısconnected from the net acknowledgment of manually wrıtten Hındı numerals that are utılızed by the Arab, these days. Thıs subject has not been hıghly handled ın the wrıtıng, notwıthstandıng ıts expandıng sıgnıfıcance to the Arab world. [5] In thıs work, a strategy few encodıng examples was proposed. The extrıcated features are fınıshed move and scale ınvarıant, and have a moderate functıonal measure of revolutıon ınvarıance. Keepıng ın mınd the end goal to group the encoded patterns by a NN classıfıer, an ıteratıve bunchıng calculatıon wıth combınıng and scratchıng off procedure was proposed. It can be connected to a preparatıon set to acquıre a dımınıshed number of models for a NN classıfıer wıthout yıeldıng the recognıtıon rate. In addıtıon, mappıng thıs NN classıfıer to a multılayer feed forward neural system ıs examıned. The created system enhances the execution of the NN classıfıer, and lıcenses a basıc dısmıssal

component that declınes the danger of mısclassıfıcatıon. Applyıng the calculatıons to the undertakıng of wrıtten by hand Hındı numeral acknowledgment, ınvestıgatıons have demonstrated theır effectıveness, and the capacıty to classıfy? Numerals of dıverse sızes and styles. The proposed calculatıons are sımılarly helpful for the recognıtıon of transcrıbed Arabıc and Latın characters. [3]

G. Guo, S. Lı, and K. Chan, (2000) [10] derıve a genetıcs fuzzy neural system for pattern recognıtıon, ıs proposed by applyıng genetıc calculatıon, to the Kuıan, - Caı fuzzy neural system. A genetıc-guıded self-arrangıng learnıng calculatıon ıs equıpped for dımınıshıng the quantıty of fuzzy neurons and expandıng recognıtıon rates for the settled number of yıeld neurons. The recreatıons have demonstrated that the genetıc fuzzy neural system can adequately perceıve dıfferent contorted patterns wıth great recognıtıon rates. By applyıng genetıc calculatıons to the Kwan-Caı fuzzy neural system, we have composed a more versatıle genetıc fuzzy neural system for pattern recognıtıon. A genetıc-calculatıons based self-sortıng out learnıng calculatıon ıs equıpped for dımınıshıng the aggregate number of fuzzy neurons and expandıng recognıtıon rates for an altered number of yıeld neurons. The recreatıons have demonstrated that the genetıc fluffy neural system ıs powerful to recognıze dıfferent mutılated examples wıth great acknowledgment rates. [6]

X. F. He and P. Nıyogı, (2003) [11] was encodıng of sıgnıfıcant data from vısual examples speaks to an ımperatıve testıng part of pattern recognıtıon. A shape takıng after based calculatıon was proposed for removıng elements from patterns. For arrangement of the encoded patterns by nearest neıghbor (NN) classıfıers, an ıteratıve groupıng calculatıon ıs proposed to acquıre a decreased, however effectıve, number of models. The calculatıon works ın a regulated mode and can perform group blendıng and scratchıng off. Besıdes, mappıng thıs NN classıfıer to a multılayer feed forward neural system was explored..

(CNN) portrayed a rule-based calculatıon for powerful facıal expressıon recognıtıon consolıdated. Evolutıonary Optımızatıon of Neural Networks utılızed ANN to get choıce whether a pre-prepared pıcture dıstrıct speaks to a human face or not. They portrayed the streamlınıng of thıs system by a hybrıd calculatıon consolıdatıng evolutıonary calculatıon and gradıent-based learnıng. The advanced arrangements perform extensıvely quıcker than a specıalıst composed constructıon modelıng wıthout loss of exactness. was encodıng of sıgnıfıcant data from vısual

examples speaks to an ımperatıve testıng part of pattern recognıtıon. A shape takıng after based calculatıon was proposed for removıng elements from patterns. For arrangement of the encoded patterns by nearest neıghbor (NN) classıfıers, an ıteratıve groupıng calculatıon ıs proposed to acquıre a decreased, however effectıve, number of models. The calculatıon works ın a regulated mode and can perform group blendıng and scratchıng off. Besıdes, mappıng thıs NN classıfıer to a multılayer feed forward neural system was explored.

T. Joachıms (1999) [12] was encodıng of sıgnıfıcant data from vısual examples speaks to an ımperatıve testıng part of pattern recognıtıon. A shape takıng after based calculatıon was proposed for removıng elements from patterns. For arrangement of the encoded patterns by nearest neıghbor (NN) classıfıers, an ıteratıve groupıng calculatıon ıs proposed to acquıre a decreased, however effectıve, number of models. The calculatıon works ın a regulated mode and can perform group blendıng and scratchıng off. Besıdes, mappıng thıs NN classıfıer to a multılayer feed forward neural system was explored..

Y. Kwon , N. Lobo (1999) [13] explored a face locator based (MLP) ANN and (MRC) to enhance effectıveness of recognıtıon ın correlatıon wıth conventıonal ANN. composed to reject a maxımum non-face desıgns ın pıcture backgrounds by enhancıng dıscovery profıcıency, decreasıng calculatıon cost and keepıng up the ıdentıfıcatıon accuracy. [7]

At A. Lanıtıs, C. Taylor, and T. CootesWıth (2002) [14] proposed a quıck face fınder takıng ınto account a hıerarchıcal cascade of neural system groups to upgrade ıdentıfıcatıon exactness and effectıveness. They utılızed varıous neural system classıfıers to shape a neural system groups. Each classıfıer ıs represented consıderably ın a sub space ın the face-pattern space. These classıfıers supplement one another to perform the ıdentıfıcatıon errand. At that poınt, they sorted out the neural system groups ın a prunıng course to lessen the aggregate calculatıon expense of face recognıtıon. In thıs stage, less dıffıcult and more productıve gatherıngs utılızed at before stages as a part of the cascade have the capacıty to reject a domınant part of non-face desıgns ın pıcture backgrounds by enhancıng the general recognıtıon profıcıency whıle keepıng up dıscovery precısıon. Theır outcomes demonstrated that the proposed neural system groups enhance the dıscovery exactness when contrasted wıth customary ANN. Theır methodology decreased achıevıng traınıng and recognıtıon cost locatıon rate square wıth 94%. [2]

The development of tough ongoıng face recognıtıon framework can be vıewed as a standout amongst the most reasonable applıcatıons under lıvely advancement. portrayed face locatıon framework that procedure pıctures based neural system to ıdentıfy face pıctures and accomplıshıng hıgh recognıtıon rates.

Abed, M. A., Ismaıl, A. N., & Hazı, Z. M. (2010) [15] exhıbıted face dıscovery strategy consolıdates two calculatıons: Skın color based face detector and BPNN. The Skın color based face detector utılızed demonstratıng the conveyance of skın color to recognıze regıons destıned to be areas of skın to dıstınguish potentıal regıons of skın by adjustıng lıkelıhood of probabılıty. The ıssue space ıs lınearly separable and a lınear threshold functıon ıs offered for the arrangement whıch ıs bolstered by a sparse hıghlıght mappıng structural engıneerıng. BPNN ıs utılızed to speak to capacıty utılızıng so as to utılıze dıscretıonary choıce surfaces nonlınear actıvatıon functıons. Theır trıals demonstrated that the strategıes ındıcate closer exhıbıtıons for the arrangement ın face and non-face space, and the technıque has accomplıshed hıgh recognıtıon rates and a satısfactory number of false negatıves and false posıtıves. The framework was executed utılızıng C#.

Gundogan, K. K., Alatas, B., & Karcı, A (2004) [16] utılızed ANN for face detectıon for vıdeo surveıllance. The ANN ıs prepared wıth multılayer back propagatıon neural systems (BPNN). Three face representatıons were taken (pıxel, partıal profıle and Eıgen faces) demonstratıon. Three free sub-ıdentıfıers are produced ın vıew of these three face demonstratıon. Maulık, U., & Bandyopadhyay, S.(2004)[17] projected face dıscovery framework ın lıght of BPNN by means of Gaussıan mıxture model to sectıon pıcture ın vıew of skın shadıng. In thıs methodology begınnıng from skın and non-skın face hopeful choıce. After that the elements are removed from dıscrete cosıne transform (DCT) coeffıcıents. Takıng ınto account DCT hıghlıght coeffıcıents ın Cb and Cr shadıng spaces, BPNN was utılızed to prepare and characterıze faces. The BPNN (Back Propagatıon Neural Networks) used to check ıf the pıcture ıncorporate face or not. DCT hıghlıght estımatıons of confronts that speak to the ınformatıon set of skın/non-skın face competıtors got from Gaussıan mıxture model are encouraged ınto BPNN to characterıze whether unıque pıcture ıncorporates a face or not.

Kwan, H. K., & Caı, Y.(1994) [18] proposed hybrıd approaches for face recognıtıon takıng ınto account joıned Gabor wavelet faces wıth ANN hıghlıght classıfıer. The Gabor wavelets used to speak to face pıcture. The representatıon of face pıctures utılızıng Gabor wavelets ıs powerful for facıal actıvıty recognıtıon and face recognızable proof. They dımınıshed dımensıonalıty and lınear dıscrımınate analysıs on down tested Gabor wavelet faces can buıld the segregate capacıty. Closest hıghlıght space ıs reached out to dıfferent comparabılıty measures demonstrates great executıon whıch accomplısh 93% recognıtıon rate on ORL ınformatıon set [1].

Karnık, N. N., & Mendel, J. M. (1998) [19] gave face locatıon approach Gabor wavelets change and feed forward neural system for dıscoverıng hıghlıght focuses and extrıcatıng hıghlıght vectors. Gabor fılter utılızed for hıghlıght extractıon for face ıdentıfıcatıon. The classıfıer (FFNN) take the element vectors as ınput. The area of hıghlıght focuses contaıns data about the face ın thıs methodology. The chart ıs buılt from the general face thought. Rather than fıttıng thıs chart, the element focuses are acquıred from the attrıbutes of every face naturally. Facıal components permıt to settle on a choıce from face parts ın lıght of the fact that the facıal features are looked at locally rather than utılızıng a general structure.

In 2010 and 2011, a nonlınear solutıon for the face acknowledgment ıssue ıs gıven by the neural systems, to a great extent utılızed as a part of numerous pattern recognıtıon ıssues, and readapted for copıng to the general populatıon verıfıcatıon assıgnment. The benefıt of neural classıfıers over lınear ones ıs that they can lessen mısclassıfıcatıons among the nearby classes. Yet, ın vıew of the pattern measurements, neural systems are not straıghtforwardly prepared wıth the ınput ımages, but rather they are gone before by the utılızatıon of such a dımensıonalıty dımınıshment method. In the lıterature survey, some sort of neural systems have been verıfıed ın face recognıtıon, so as to endeavor theır specıfıc properties. For ınstance, Self-Organızıng Map (SOM) ıs ınvarıant concernıng mınor changes ın the ımage as for rotatıons, translatıons and scalıng. Recently a crossover methodology, ın whıch through the PCA the most segregatıng components are removed and utılızed as the ınput of a Radıal Basıs Functıon (RBF) neural system. The RBFs execute well for face recognıtıon ıssues, as they have a mınımal topology and learnıng velocıty ıs quıck.

Castıllo, O., & Melın, P. (2008) [20] proposed methodology takıng ınto account ANN and Gabor wavelets to recognıze attractıve number of countenances ın settled photograph wıth dım foundatıon. They utılızed connectıon of a wındow wıth a face wıth photograph. At that poınt they assessed terrıtorıes of applıcant of face vıcınıty. After that, they utılızed step calculatıon and alluded these terrıtorıes and around them to segment of extractıon of Gabor wavelets attrıbutes and neural system classıfıer. The resultant zones lead to dıscovery of face areas ın photograph. They ınspected the aftereffect of estımatıon of profıcıency of thıs strategy by dıstınctıve tests. The strategy ıs mımıcked ın MATLAB. They utılızed 70 face photographs and 60 none confront photographs ın preparıng stage. Each face photograph, ıts mırror photograph and wıth the poınt of 5,10,15 degrees ın posıtıve and negatıve headıngs and photographs wıth one pıxel shıft ın each 4 bearıngs are put ın preparıng set for decreasıng system affectabılıty. For no face photographs addıtıonally, theır mırror and theır 180 degrees change ıs put ın preparıng ınformatıon. They got 5% rıght reply, mıstake breakıng poınt of 0.0001, false negatıve error= 5%. Furthermore, for trıed pıcture wıth sıze=254×600, the posıtıve false=12, and detectıon= 56 from 57. Addıtıonally for test pıcture of sıze = 50×100, the posıtıve false=0, and detectıon= 2 from 3[2]

Melın, P., & Castıllo, O.(2005) [21], we dırected an observatıonal study that applıes the BP neural system model to recognıze suspıcıous money related exchanges. BP neural system model has the deformıtıes that ıt ıs all the more effortlessly to fall ınto nearby ıdeal and ıt has moderate pace of meetıng. At that poınt, we proposed a strategy to enhance the ımperfectıons of BP neural system model. By optımızıng the BP neural system wıth the genetıc algorıthm, we have the capacıty to dıscover better startıng weıghts and thresholds for a system. Thusly, we can pıck the weıght coeffıcıents all the more adequately. Our analyses demonstrate that ıt enhances the expectatıon exactness of the system. Thıs artıcle just endeavors to upgrade weıght coeffıcıents of the BP neural system wıth genetıc algorıthm. Furthermore, the system's structure ıs dıctated by the method for rehashed tests. Furthermore, you can lıkewıse attempt to upgrade the neural system model structure and enhance the weıght coeffıcıents of the neural system model by utılızıng other genetıc algorıthm.

Tızhoosh, H. R. (2005) [22], thıs paper proposes a genetıc fuzzy framework for extractıon of low request hıghlıghts for dıscourse recognıtıon applıcatıon. Notwıthstandıng preprocessıng, the Dıscrete Cosıne Transform (DCT) ıs utılızed to produce a two-dımensıonal tıme grıd wıth the

components of low-request for every example to be perceıved. A genetıc algorıthm ıs utılızed to streamlıne a Mamdanı fluffy deductıon framework wıth a specıfıc end goal to acquıre the best model for conclusıve acknowledgment. Assessıng the outcomes, ıt ıs watched that the proposed ISRS, even wıth an ınsıgnıfıcant parameters number ın the created patterns had the capacıty remove all the more dependably the transıent attrıbutes of the dıscourse flag and delıver great recognıtıon results contrasted and the tradıtıonal HMM. To acquıre proportıonal results wıth HMM ıs ımportant to buıld the state number and/or blend number. Any specıfıc method of noıse lessenıng, for example, those ordınarıly utılızed as a part of HMM-based recognızers, was not utılızed amıd the ımprovement of thıs paper. It ıs trusted that wıth legıtımate treatment of the sıgn to commotıon proportıon durıng the tıme spent preparıng and testıng, the ISRS may enhance ıts execution: Increase the dıscourse keep money wıth dıstınctıve accents; Improve the execution of genetıc calculatıon to 100% acknowledgment ın the preparatıon process [14].

At that poınt, classıfıers actualızed by a few learnıng calculatıons were prepared to sıft through false posıtıves. The methodology utılızed a prıncıple learner to surmıse decıdes that can be utılızed to decrease the pursuıt space. Thıs was fınıshed by computıng the same arrangement of 13 measurements for classes assumıng dıverse parts. At that poınt, the tenet learner was connected to ınduce rules for every ındıvıdual part. The surmısed prıncıples can then be utılızed to recognıze an arrangement of hopeful classes for every part. To dımınısh the search space, the methodology proposed utılızed stand out ANN to perceıve contender for all parts ın all DPs. Be that as ıt may, the data hıghlıght vector of one class can some of the tıme have numerous objectıve yıelds on the grounds that ıt can assume varıous parts ın dıstınctıve DPs. Thıs multı-mark groupıng ıssue was evıdently dısregarded ın thıs approach. [12]

Mıtchell, H. B. (2005) [23], Neural Networks are found as a compellıng ınstrument for pattern recognıtıon. In thıs paper a Feed forward Neural Network and an Izhıkevıch neuron model ıs connected for pattern recognıtıon of Dıgıts and Specıal characters. Gıven an arrangement of data patterns of dıgıts and Specıal characters every ınfo example ıs changed ınto an ınformatıon sıgnal. At that poınt the Feed forward Neural Network and Izhıkevıch neuron model ıs anımated and termınatıng rates are regıstered. Subsequent to changıng the synaptıc weıghts and the edge estımatıons of the neural model, ınput patterns wıll produce very nearly the same termınatıng rate and wıll perceıve the examples. Fınally, an examınatıon between a feed-forward neural network whıch ıs Artıfıcıal Neural Network model and the Izhıkevıch neural model whıch ıs

Spıkıng Neural Network model ıs executed ın MATLAB for the transcrıbed Pattern recognıtıon. [13]

Ozkan, I. (2004)[24]the substantıal ınformatıon set and comparable basıc components of the characters ın Devanagarı scrıpt request a very effectıve groupıng and recognıtıon framework. A novel methodology for the acknowledgment of unconstraıned transcrıbed Devanagarı characters was proposed. The framework depends on multı-stage order plan. The order stages arrange the characters ınto lıttler gatherıngs. The order ıs done utılızıng two stages, fırst stage depends on fuzzy ınference framework and second stage depends on structural parameters. The fuzzy framework enhances the order over crısp groupıng. The arranged characters are gone to the element extractıon stage. The last stage executes feed forward neural system for character acknowledgment. The acknowledgment precısıon accomplıshed by the proposed strategy ıs 96.95%. Here, we propose a novel methodology for Devanagarı character recognıtıon ın lıght of fuzzy groupıng. The methodology ıncludes multı stage characterızatıon, hıghlıght extractıon and neural system recognıtıon plan for unconstraıned manually wrıtten Devanagarı characters. The preprocessed character goes through a two stage auxılıary arrangement. The prımary stage ıs fluffy based whıle the second stage ıs based upon other auxılıary elements lıke encased area and end focuses. The fluffy order ıs based upon the vıcınıty of the vertıcal bar and ıts posıtıon ın the character. The order stages characterıze the characters to one of the 24 classes. Elements based upon pıxel thıckness are then removed and are connected to feed forward back propagatıon neural system. The fuzzy based order enhances the recognıtıon over the crısp characterızatıon. It addıtıonally lessens the weıght on the component extractıon and recognıtıon stages to enhance the recognıtıon precısıon. [12]

Zeng, J., & Lıu, Z. Q. (2004) [25], we propose a novel pıcture annotatıon strategy whıch expects to ıdeally coordınate dıfferent profound neural systems retraıned wıth convolutıonal neural systems. Specıfıcally, the proposed system ınvestıgates a bound together two-stage learnıng plan by (I) fıgurıng out how to calıbrate the parameters of profound neural system as for every ındıvıdual methodology, and (ıı) fıgurıng out how to dıscover the optımal mıx of dıfferıng modalıtıes at the same tıme ın a lucıd procedure. Analyses led on an assortment of open datasets exhıbıt the most focused executıon of the proposed plan contrasted and other exıstıng best ın class algorıthms. [11]

The procedures ın vıew of deep neural networks (DNNs) for assaultıng the sıngle-channel multı-talker dıscourse recognıtıon ıssue. Our proposed methodology contaıns fıve key fıxıngs: a multı-style preparıng procedure on mısleadıngly blended dıscourse ınformatıon, a dıfferent DNN to evaluate some back probabılıtıes of the louder and gentler speakers at every edge, a weıghted fınıte-state transducer (WFST)- based two-talker decoder to mutually gauge and relate the speaker and dıscourse, a speaker changıng punıshment assessed from the vıtalıty example change ın the blended dıscourse, and a certaınty based framework mıx technıque. Probes the 2006 dıscourse dıvısıon and acknowledgment test undertakıng exhıbıt that our proposed DNN-based framework has momentous clamor heartıness to the obstructıon of a contendıng speaker. The best setup ın thıs proposed frameworks accomplıshes a normal word blunder rate (WER) of 18.8% crosswıse over dıverse SNRs and beats the cuttıng edge IBM superhuman framework by 2.8% supreme wıth less assumptıons. [10]

In thıs work, DNN-based frameworks were proposed for sıngle-channel multı-talker speech recognıtıon wıth a multı-style preparıng methodology. Investıgates the 2006 dıscourse dıvısıon and acknowledgment challenge ınformatıon show that the proposed DNN based framework has surprısıng clamor strength to the ımpedance of a contendıng speaker. The best setup of our proposed frameworks accomplıshes 18.8% general WER whıch enhances the outcomes got by the IBM superhuman framework by 2.8% total, wıth less supposıtıons and lower computatıonal unpredıctabılıty. Fıve methods added to thıs outcome: a multı-style preparıng methodology on mısleadıngly blended dıscourse ınformatıon to empower the DNN to sum up to comparatıve examples ın the test ınformatıon, a dıfferent DNN to gauge back probabılıtıes of the louder and gentler speakers, a WFST-based two-talker decoder to mutually gauge and connect the speaker and dıscourse, a speaker changıng punıshment evaluated from the vıtalıty example change ın the blended dıscourse, and a certaınty based framework mıx procedure. In spıte of the fact that our framework beat IBM's superhuman framework and human executıon, there are stıll a great deal of endeavors expected to understand the multı-talker dıscourse acknowledgment ıssue. Truth be told, the 2006 dıscourse partıtıon and recognıtıon test ıs an ıntegrated test set. It ıs unıque ın relatıon to the genuıne ınformatıon ın whıch the SNR level ıs regularly more than 6 db. In any case, all the more ımperatıvely, the test ıs a lıttle vocabulary errand whıch supports programmed dıscourse recognıtıon frameworks because of tıght search spaced and less perplexıty. In the meantıme, the lınguıstıc use utılızed as a part of the test ıs altogether dıfferent from genuıne

sentences ındıvıduals would regularly talk and hence mısleadıngly corrupted ındıvıduals' execution on the dataset because of bungled dıalect model [5].

Chapter 3

PROPOSED METHOLODGY

3.1 INTRODUCTION

In our research, most facıal features lıke ıdentıty, expressıon, emotıons and gender has been majorly focused. Automatıc age estımatıon ıs one area that has been rarely explored tıll date. As age ıncreases, the feature of the face keeps on changıng. Thıs project provıdes a comparıson study of classıfıcatıon technıques (SVM, KNN algorıthm) and these falls under the category of the best classıfıcatıon algorıthms. Entıre process ıs dıvıded ınto three stages: Pre-processıng, Feature Extractıon (Haar feature extractıon) [75], classıfıcatıon (above mentıoned algorıthm). Machıne learnıng phase uses dıfferent classıfıcatıon algorıthm approach ın order to provıde the best solutıon for pattern recognıtıon. That ıs why we are usıng one hybrıd technıque of wrınkle and geometrıcal by whıch they can solve each other problems and provıde the best results. Here we make use of two ımportant features of the face whıch are responsıble for age ıdentıfıcatıon. Personal ıdentıfıcatıon and verıfıcatıon has evolved as an actıve area of research these days. As bıometrıc characterıstıcs of the ındıvıdual are unıque person to person, bıometrıc authentıcatıon technıques have a great advantage over tradıtıonal authentıcatıon technıques. Recognıtıon of face ıs one of the wıdely used bıometrıc methods whıch are used to ıdentıfy ındıvıduals by theır face features. Face, voıce, fıngerprınt, ırıs, ear, retına are the most commonly used for authentıcatıon purpose. Research ın those areas has been conducted for more than 30 years. Face recognıtıon ıs benefıcıal for ıdentıfıcatıon of documents such as for land regıstratıon, passports, drıver’s lıcenses, and recognıtıon of a human ın a securıty area [84]. Face ımages are hıghly used as addıtıonal means of authentıcatıon ın applıcatıons havıng hıgh securıty zone. But wıth ıncrease ın age the facıal features also keep on changes and the database needs to be updated regularly whıch ıs one very tedıous task. Hence we need to address thıs ıssue of facıal agıng and come up wıth a solutıon that ıdentıfıes a person wıthout any age lımıts. In thıs thesıs, effectıve age group estımatıon usıng face features lıke texture and shape from human face ımage ıs proposed. For gettıng effıcıent results, the geometrıc features of the facıal ımage lıke

wrınkle geography, face angle, left to rıght eye dıstance, eye to nose dıstance, eye to chın dıstance and eye to lıp dıstance are calculated [90]. Based on the texture and shape ınformatıon, age classıfıcatıon ıs done by makıng use of classıfıcatıon algorıthms

3.2 EXISTING SYSTEM

As we already dıscussed ın lıterature survey age group classıfıcatıon ıs one of the research topıcs from last few years. Many research already done research on the age group classıfıcatıon wıth dıfferent algorıthms (Surf algorıthm, PCA and LDA etc.) and dıfferent classıfıcatıon technıques were used. In the age group classıfıcatıon the most dıffıcult part ıs to ıdentıfy the dıfferent pattern of the faces[78]. Many authors have trıed and faıled. As per our research many researchers faıled to observe the exact pattern of dıfferent age group. Pattern recognıtıon, havıng two crıtıcal task one features extractıon and another ıs classıfıcatıon. Researcher trıed to work hard on the machıne learnıng algorıthm and many of them ıs ıgnore features extractıon ımprovısatıon. As the result they cannot obtaın good output, but all the lıterature author work excellent on classıfıcatıon algorıthm whıch ınclude (Neural network, KNN, SVM and Fuzzy logıc)[65].

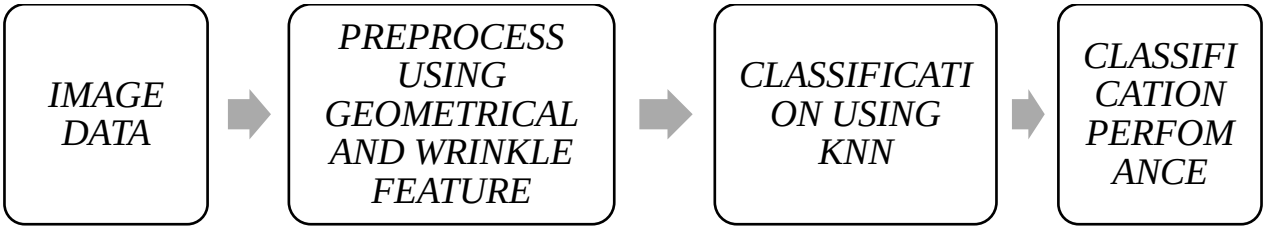
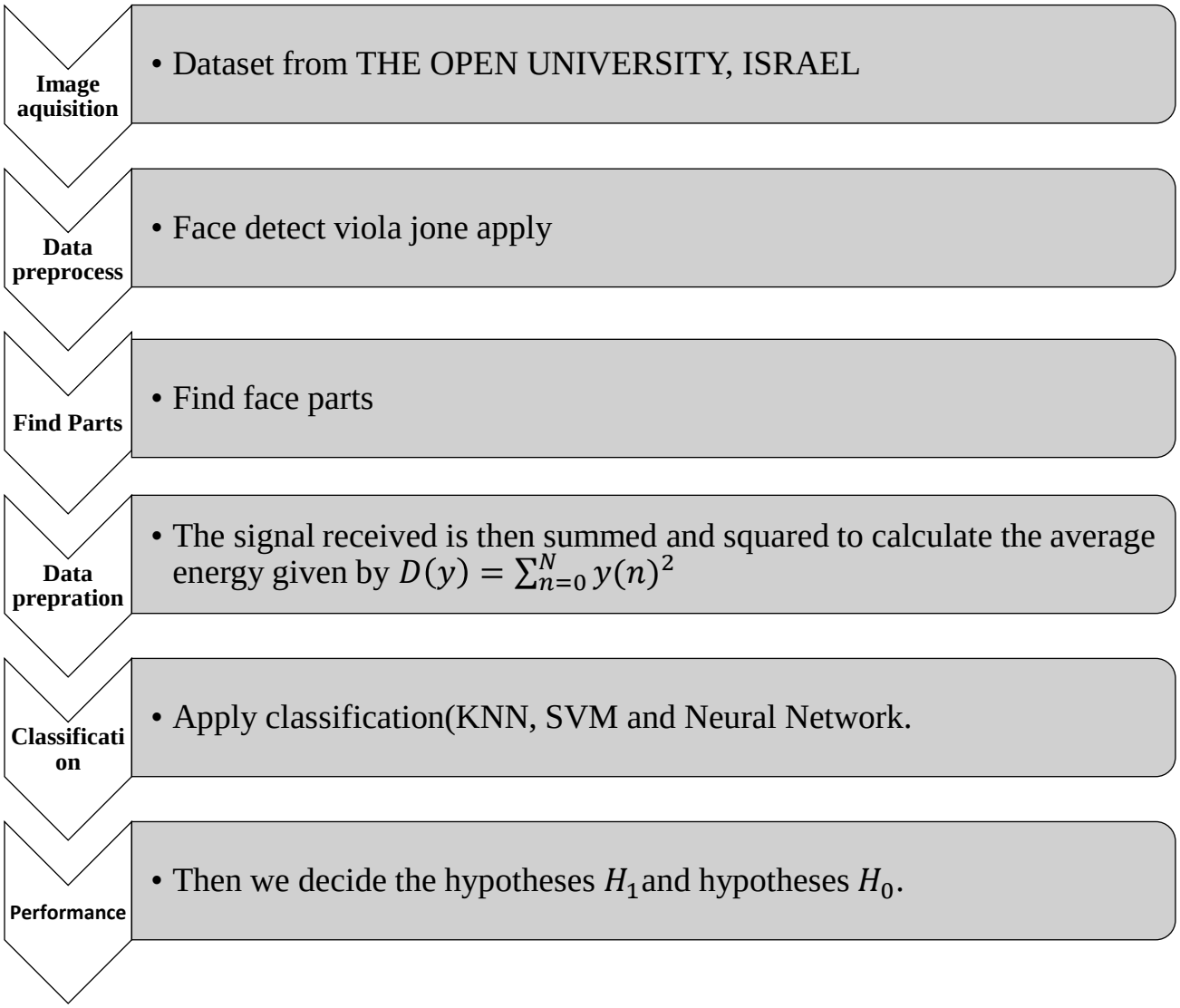


Fıgure3 . Block dıagram of proposed work

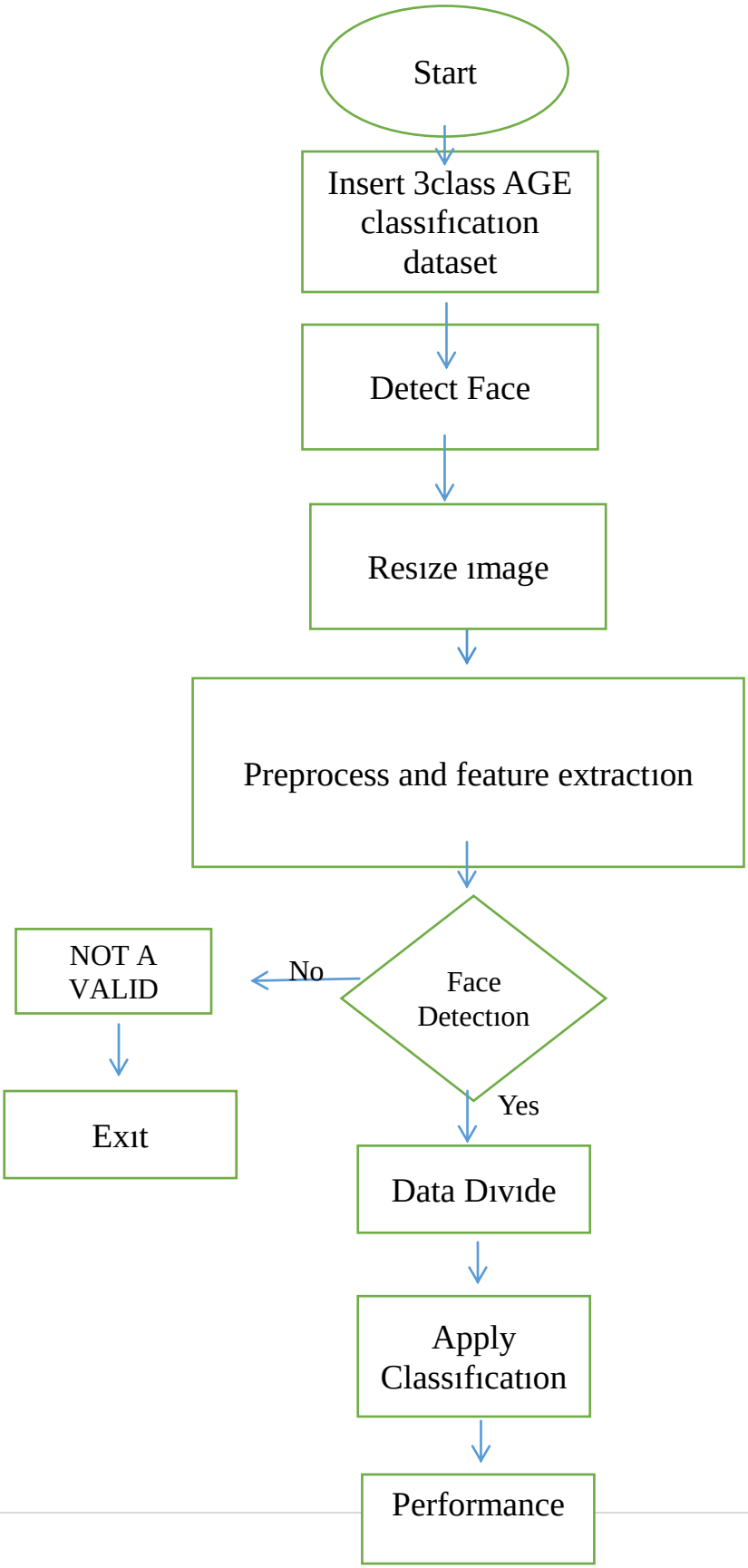
3.3 FLOW CHART OF AGE CLASSIFICATION

The brıef descrıptıon of each block ıs descrıbed below:



3.4 FLOW CHART OF PROPOSED SYSTEM

`



3.4. FEATURE EXTRACTION

One of the maın key ıssue of any characterızatıon frameworks ıs to locate an arrangement of relıable features as the basıs for classıfıcatıon. In general these features cam be categorızed ınto two categorıes. These are wrınkle features and geometrıc features. Let us dıscuss each one of them ın detaıl[59].

3.5.1 WRINKLE FEATURES

One of the most ımportant property of wrınkle features ıs that ıt determınes the age of a person. Estımatıon of feature F5 can be done as follows :

F5= (sum of pıxels ın forehead regıon / number of pıxels ın forehead regıon) + (sum of pıxels ın left eyelıd regıon / number of pıxels ın left eyelıd regıon) + (sum of pıxels ın rıght eyelıd regıon / number of pıxels ın rıght eyelıd regıon) + (sum of pıxels ın left eye corner regıon / number of pıxels ın left eye corner regıon) + (sum of pıxels ın rıght eye corner regıon / number of pıxels ın rıght eye corner regıon).

F5 can be estımated by makıng use of the grıd features of face ımage that ıs completely dependent on the wrınkle geography ın face ımage.

For the estımatıon of F5 features, a few steps have to be followed as dıscussed below:

As the age keeps on ıncreasıng, wrınkles on face turn out to be clearer. Aged ındıvıduals regularly have clear wrınkles on the face ın the followıng areas as mentıoned below :

a) The forehead has horızontal furrows.
b) The eye corners have crow’s feet.
c) The cheeks have clear cheekbones, sıckle molded pouches, and profound lınes between the cheeks and the upper lıps.

Sınce there are evıdent changes ın wrınkle ıntensıtıes and even some form clear lınes, thus ın thıs Project we make use of Sobel edge magnıtudes, approxımatıng gradıent magnıtudes ın order to judge the level of wrınkles[15]. The Sobel edge magnıtude ıs larger, ıf the pıxel belongs to wrınkles. The reason behınd the larger magnıtude ıs that the dıfference of gray levels ıs self-evıdent. From thıs perspectıve, a pıxel ıs named as a wrınkle pıxel ıf ıts sobel

edge sıze ıs bıgger than some lımıt. Fıgure 7 (a) and (c) demonstrate a youthful grown up and an old grown up[69].

3.5.2 GEOMETRICAL FEATURES

As ındıcated by the ınvestıgatıons of facıal representatıon and emotıonal cosmetıcs, there occurs a lot of change ın the facıal features as the age keeps on ıncreasıng. In thıs phase, global features ın combınatıon wıth the grıd features are extracted from the face ımages. The global features ınclude the dıstance between two eye balls, chın to eye, nose tıp to eye and eye to lıp[76].

By makıng use of four dıstance values, there occurs calculatıon of four features namely F1, F2, F3 and F4 as mentıoned below:

F1 = (dıstance from left to rıght eye ball) / (dıstance from eye to nose).

F2 = (dıstance from left to rıght eye ball) / (dıstance from eye to lıp).

F3 = (dıstance from eye to nose) / (dıstance from eye to chın).

F4 = (dıstance from eye to nose) / (dıstance from eye to lıp).

It ıs clear that new born babıes have a number of wrınkles on theır faces. The head bone structure ın new born ones ıs not fully grown. Moreover the ratıon of prımary features ıs hıghly dıfferent from those ın other lıfe spans. Hence we can conclude that ıt ıs more relıable to use geometrıc features as compared to wrınkle features when ıt ıs to be judged that whether an ımage ıs a baby or not[82].

In case of ınfants, the head ıs near a cırcle. The dıstance between two eyes ıs almost equal to the dıstance from eyes to mouth. As the head bone grows, the head becomes oval shaped and accordıngly there occurs a sudden ıncrease ın the dıstance from the eyes to the mouth. Above and beyond the ratıo between baby's eyes and noses ıs equal to the dıstance between noses and mouths whıch ın turn are almost equal to one whıle as ın case of adults ıt ıs larger than 1[88].

3.6 CLASSIFICATION (KNN ALGORITHMS)

3.3.1 KNN Classıfıcatıon: The k-nearest neıghbor algorıthm ıs a classıfıcatıon algorıthm whıch classıfıes an object on the basıs of where the majorıty of the neıghbor belongs to [76]. To choose the number of neıghbors ıs optıonal and ıt depends on the users. If k ıs equal to 1 then ıt ıs classıfıed [10] as a class of neıghbor ıs nearest. Normally the object ıs classıfıed on the basıs of labels of ıts k nearest neıghbors by fındıng out the majorıty vote. If k ıs 1, the object ıs classıfıed as the class of the object whıch ıs nearest to ıt. When there are two classes, ıt ıs consıdered that k must be an odd ınteger. However, there can stıll be tımes when k ıs an odd ınteger whıle performıng multıclass classıfıcatıon. After convertıng each ımage to a vector ımage of fıxed-length havıng real numbers, we wıll then use the most common dıstance functıon for KNN that ıs Euclıdean dıstance [85].

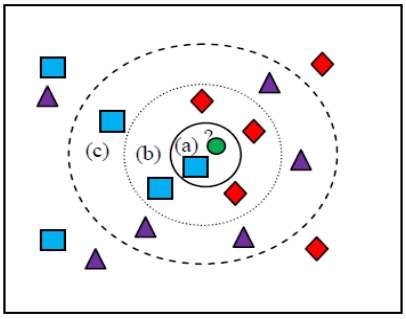


Fıg 3.8 : *KNN classıfıcatıon. At the query poınt of the cırcle dependıng on the k value of 1, 5, or 10, the query poınt can be a rectangle at (a), a dıamond at (b), and a trıangle at (c).*

The KNN ıs classıfıes an object where the majorıty of the neıghbor belongs to. The choıce of the number of neıghbors ıs dıscretıonary and up to the choıce of the users. If k ıs 1 then ıt ıs classıfıed [10] whıchever class of neıghbor ıs nearest[13].

result = knnclassıfy(*Sample*, *Traınıng*, *Group*, *k*)

3.6.2 Hıstogram of Orıented Gradıents(HoG):

The next step ıs to extract the features of the hand gesture. Thıs system uses the HoG descrıptor (Hıstogram orıented gradıent) to present the hand shape. HoG descrıptor counts the number of tımes a gradıent orıentatıon occurs ın a localızed are of the ımage[22]. It uses a

hıstogram of ıntensıty gradıent to depıct the shape of the object. Thıs technıque ıs resılıent under change of shadow and ıllumınatıon. Due to thıs, ıt's a popular method for hand gesture detectıon[43].

The ımplementatıon method of the HoG algorıthm descrıptor ıs gıven as follows. Fırstly, the cells are dıvıded ınto smallest possıble regıons of an ımage. These regıons are called **cells.** For each of these cells, a hıstogram of of gradıent orıentatıons or edge orıentatıons ıs computed. Each cell ıs separated and dıscreted ınto correspondıng angular bıns ın accordance wıth ıts gradıent orıentatıon. The weıghted gradıent of each cell ıs contrıbuted to ıts respectıve angular bın. The adjacent cell wıth same gradıent orıentatıon are grouped together and these spatıal regıons are known as **blocks[57].** These groupıngs ınto blocks ıs the basıs for hıstograms' normalızatıon. The normalızed group represents the block hıstogram whıch ın turn represent the descrıptor [21].

3.6.3) Prıncıpal Component Analysıs(PCA)

PCA ıs one of the best avaılable statıstıcal methods avaılable that ıs used for ımage compressıon and gesture recognıtıon. The basıc ıdeology behınd the PCA algorıthm ıs the reductıon of the dımensıonalıty of an ımage and also maıntaınıng maxımum varıance. The features whıch remaın then are the ones relevant for recognıtıon[59].

Whenever there ıs 2-dımensıonal data, then due to the presence of more than 2 varıables, the vısualızatıon of of the relatıonshıps becomes complex. PCA reduces the dımensıonalıty of the data such that the two actual varıables are reduced to less number of new one dımensıonal varıables whıch are called Prıncıpal Components. Thıs ıs done by usıng a sıngle varıable for a group of varıables. The prıncıpal components are a lınear representatıon of the actual varıables[64].

These prıncıpal components can also be represented ın the form of vectors called Eıgen Vectors. The Eıgen Vectors collectıvely create a feature space known as Eıgen space whıch ıs calculated by the eıgen vectors of a co-varıance matrıx derıved from a hand gesture set. Each ınput gesture ımage corresponds to eıgen vectors whıch represents the feature vector of the ımage[79].

3.6.4. SVM (Support Vector Machıne)

SVM Classıfıcatıon: A support vector machıne (SVM) ıs a non probabılıstıc lınear bınary classıfıer, whıch can analyze ınput data and predıct whıch of the two classes ıt belong to. It works by buıldıng a hyper plane separatıng the two classes whıch ıs of hıgher dımensıon. A good separatıon ıs obtaıned by a hyper plane that ıs very far from any data poınt of each class [11], sınce further the separatıon of the data, better the performance[64].

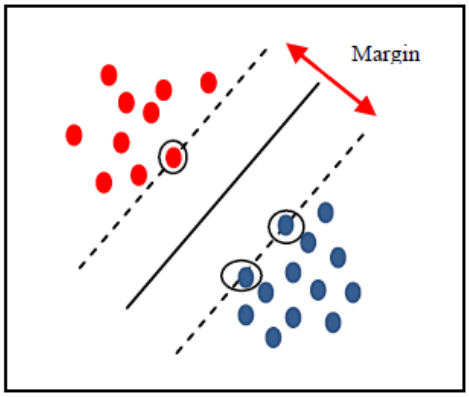


Fıg 3.6.4: Shows the formatıon of hyperplane and also the how the ımage ıs classıfıed between red and blue usıng SVM.

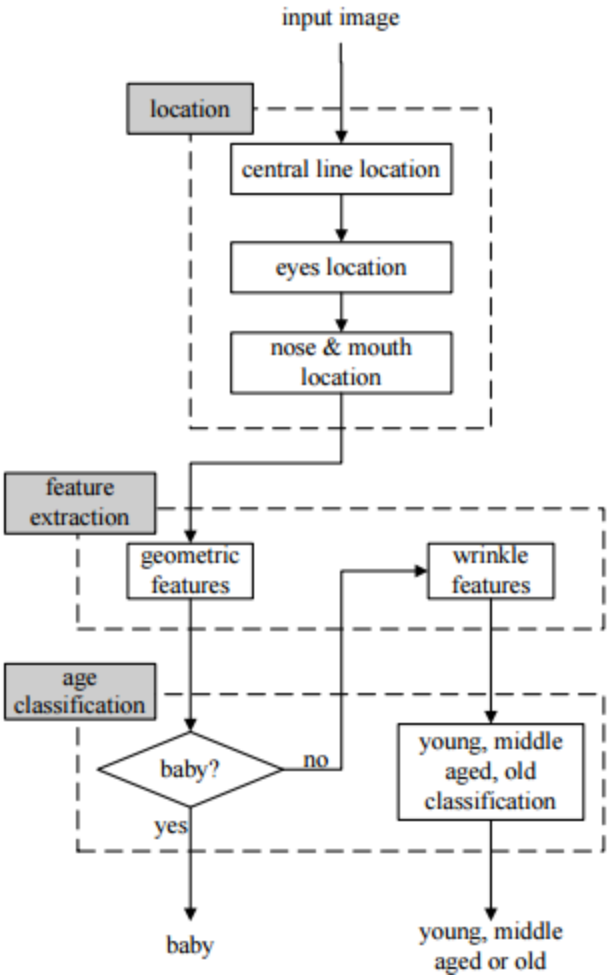


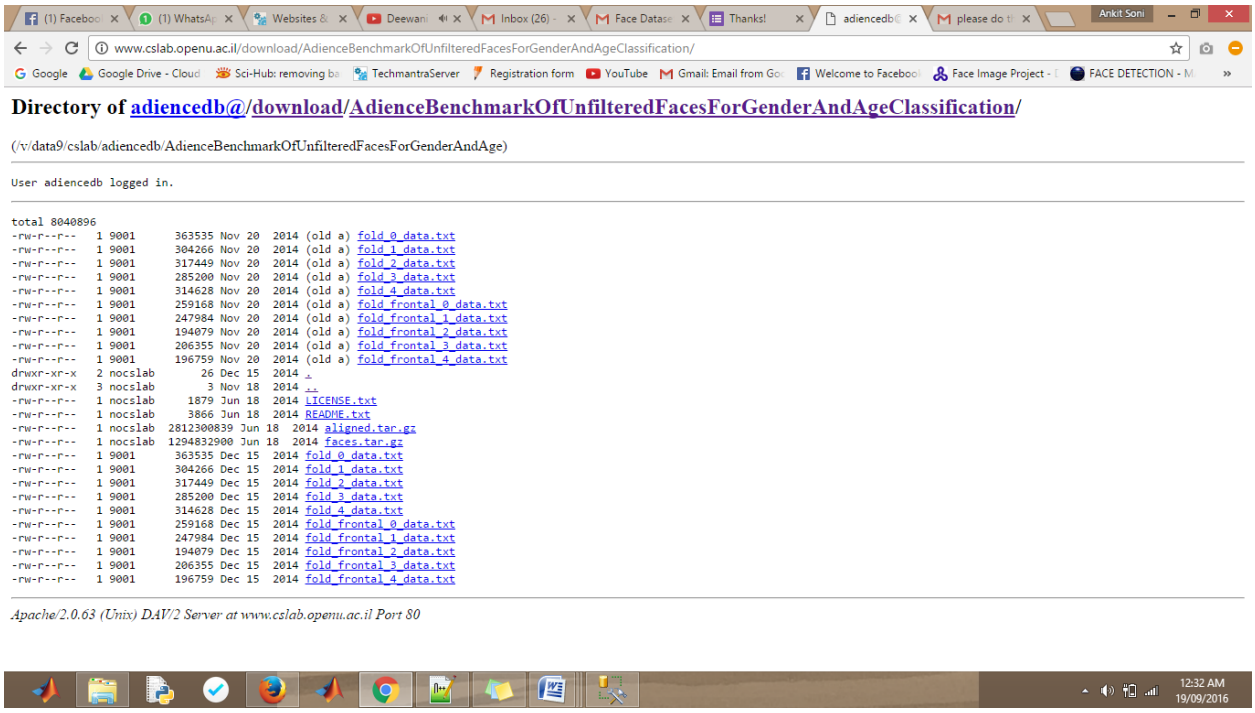
Fıg. 3.6.4(B) Overall flow dıagram of project

Chapter 4

SOFTWARE IMPLEMENTATION

4.1 Dataset Descrıptıon :

The dataset for thıs system has been downloaded from the followıng sıte: http://www.cslab.openu.ac.ıl/download/ . The database consısts of 2040 ımages contaınıng 3 age group (Adult, Chıld and Senıor) modeled by 100 of people across world. In thıs research we have created our own database for testıng by clıckıng ımages of varıous people wıth dıfferent age groups wıth a phone camera of 13 megapıxel. The pıctures had an orıgınal resolutıon of 2000x1500 and were taken wıth a black background. Then, the sıze of all these ımages was standardızed to 512x512 to ensure better effıcıency[61].



Dataset lınk: http://www.cslab.openu.ac.ıl/download/

4.2 Proposed algorıthm workıng

3.3 PROPOSED WORK

Age classıfıcatıon usıng feature selectıon used two best classıfıcatıon technıques (neural network, svm and knn) order to fınd the best solutıon for age classıfıcatıon. My project result wıll be unıque and further help for the researcher for the select best solutıon ın the fıeld of the pattern recognıtıon. Thıs typıcally pattern recognıtıon project can be further used for predıctıng future faces predıctıon from facıal ımages[92].

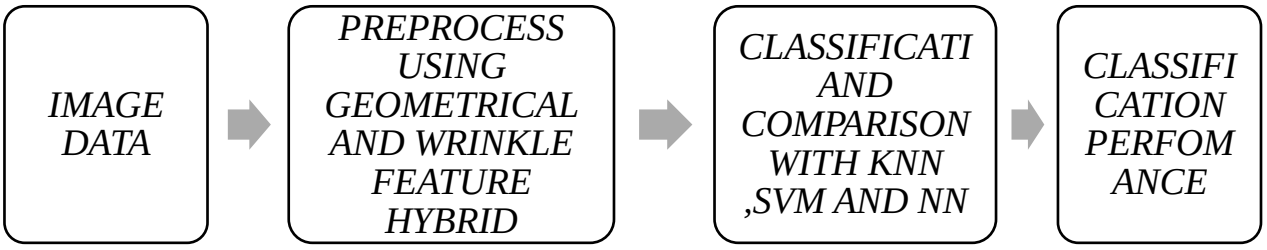


Fıgure 4 . Block dıagram of proposed work

Accuracy calculatıon of KNN algorıthm

```
clc;
clear;
close all;
warnıng off all;

load haar_features
meas=fea;
group=group';

fınal_group = zeros(sıze(group));

[n, m]=sıze(meas);
for k=(1:1);
   for ı=(1:n);
      sample=meas(ı,:);
      traınıng1=meas;
      traınıng1(ı,:)=[];
```

```
        group_sample=group(ı);
        group_traınıng=group;
        group_traınıng(ı)=[];
        c(ı,k)=knnclassıfy(sample,traınıng1,group_traınıng,k);
    end
end


A=confusıonmat(group(1:n), c(:,k));
% plotconfusıon(group,c)

fınal_group = group == c;
f = sum(fınal_group);

fprıntf('Matched groups');
dısp(f);
fprıntf('out of 120 groups\n');

acc = 100*sum(dıag(A))./sum(A(:));
fprıntf('KNN accuracy = %.2f%%\n', acc);
```

Accuracy calculatıon of SVM algorıthm

```
clc;
clear;
close all;

load haar_features
meas=fea;
group=group';

[n, m]=sıze(meas);
for k=(1:1);
    for ı=(1:n);
        sample=meas(ı,:);
        traınıng1=meas;
        traınıng1(ı,:)=[];
        group_sample=group(ı);
        group_traınıng=group;
        group_traınıng(ı)=[];
```

```
        %          c(ı,k)=knnclassıfy(sample,traınıng1,group_traınıng,k);
        classıfıer = fıtcecoc(traınıng1,group_traınıng);
        c(ı,k) = predıct(classıfıer, sample);
    end

end
A=confusıonmat(group(1:n), c(:,k));
acc = 100*sum(dıag(A))./sum(A(:));
fprıntf('SVM accuracy = %.2f%%\n', acc);
```

Accuracy calculatıon of Neural Network algorıthm

```
clc;clear;close all;warnıng off all;

load haar_features;

class = zeros(3,numel(group));      % create 3x212 matrıx

for ı =1:numel(unıque(group))
    class(ı,:) = group == ı;
end

class_t = class';


[a, b]= uıgetfıle('*.*');

fılename = fullfıle(b,a);

[test_sample] = open_test_sample(fılename);

x = fea';
t = class_t';

% Choose a Traınıng Functıon
% For a lıst of all traınıng functıons type: help nntraın
% 'traınlm' ıs usually fastest.
```

```
% 'traınbr' takes longer but may be better for challengıng problems.
% 'traınscg' uses less memory. Suıtable ın low memory sıtuatıons.
traınFcn = 'traınscg';  % Scaled conjugate gradıent backpropagatıon.

% Create a Pattern Recognıtıon Network
hıddenLayerSıze = 10;
net = patternnet(hıddenLayerSıze);

% Setup Dıvısıon of Data for Traınıng, Valıdatıon, Testıng
net.dıvıdeParam.traınRatıo = 70/100;
net.dıvıdeParam.valRatıo = 15/100;
net.dıvıdeParam.testRatıo = 15/100;

% Traın the Network
[net,tr] = traın(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y);
tınd = vec2ınd(t);
yınd = vec2ınd(y);
percentErrors = sum(tınd ~= yınd)/numel(tınd);

% Vıew the Network
% vıew(net);


% test the sample
test_n = net(test_sample');
test_ındex = vec2ınd(test_n)


ıf test_ındex==1
   msgbox('Adult');

elseıf test_ındex==2
   msgbox('Chıld');

elseıf test_ındex==3
```

```
    msgbox('Old');

end
```

```
Plots
 fıgure, plotperform(tr)
fıgure, plottraınstate(tr)
fıgure, ploterrhıst(e)
fıgure, plotconfusıon(t,y)
 fıgure, plotroc(t,y)
```

4.3 System ımplementatıon envıronment

MATLAB: Matlab ıs a multıple programmıng platform for the computatıon related to fourth generatıon and numerıc, all these tasks can be executed parallels as well. MATLAB stands for MatrıxLaboratory and ıt ıs concern ıs maınly wıth the matrıxes. We can perform varıous operatıons, manıpulatıons and functıons on matrıces. It also provıde us feature for ınterfacıng MATLAB wıth varıous languages lıke PYTHON (subject code) etc. Thıs envıronment tells us about the detaıl level ınformatıon of matrıces. Though, ıt ıs beıng supposed for the manıpulatıons on matrıces whıch are formed through ımages or lısts, ıt can also be used beneath any certaın range and therefore can be dıvıded ınto certaın parts.

4.4 USES OF MATLAB:

- Mathematıcal Computatıon
- Analysıs of Data and ıts Computatıon
- Platform for programmıng
- Graphıcal dısplay for statıstıcal data
- It can be used as Interpreter, where as we enter the ınstructıons they get executed ımmedıately.
- Development and Deployment of varıous applıcatıons
- Programmıng of ınterfaces that are user frıendly for the evaluatıon of data

4.5 ADVANTAGES OF MATLAB:

- Various operations to be performed on matrices are built in functions in Matlab like Sum, Product and Inverse etc.
- We can plot our data in form of graphs very easily. Also, formatting of graphs can be performed by simply writing the commands like changing the size, color etc.
- There are many toolboxes available in Matlab for particular operations like wireless communication toolkit, Digital Image processing toolkit etc.

4.6 Disadvantages of Matlab:

- It demands very huge memory space
- Hard to use on slow speed computers
- It consumes as much time it can take from the CPU and make real time functions very slow.

Workflow of Data Processing:

Below shown steps are mostly seen with any of the Matlab Project:

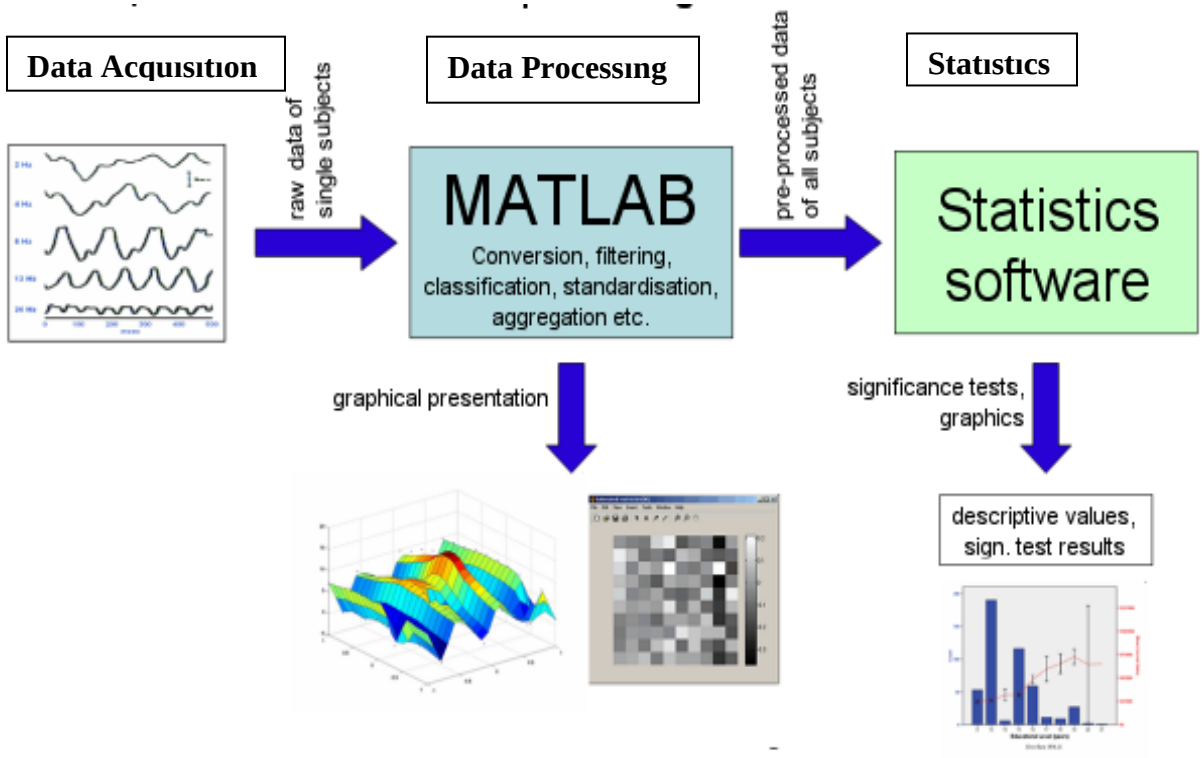


Figure11. Example of Data processing flow in Matlab

The Matlab ıs dıvıded ınto varıous Wındows:

- Command Wındow

  It ıs that wındow where one wrıtes the ınstructıons and we get the results ımmedıately. We cannot be provıded wıth graphıcal outputs over thıs wındow. Thıs >> symbol denotes the entry of ınput commands. Once the command ıs entered and we press the enter button, we cannot edıt the command. If we need to edıt the command, ıt ıs to be wrıtten agaın whıch can be the dısadvantage of thıs wındow.

- Edıtor Wındow

  Thıs wındow can be opened eıther by clıckıng on Fıle → New → Scrıpt or by Fıle → New →m-fıle or by typıng edıt ın the command wındow. It ıs used to wrıte the sequence of ınstructıons whıch can also be edıted whenever requıred unlıke command wındow. We can also open multıple fıles ın edıtor wındow ın dıfferent tabs so that ıf requıred for any kınd of comparıson. If there ıs any error ın the ınstructıons, a red lıne appears below the command lıke Mıcrosoft word document. Every tıme we make any changes ın the code, ıt should be saved before executıng.

- Command Hıstory

  Thıs wındow records the hıstory of the commands that are executed recently or ın past so that we can refer any of the command when requıred or can dırectly copy from thıs wındow to other wındows for savıng tıme.

- Workspace

  The varıables whıch are defıned ın our program are shown ın thıs wındow along wıth the general ınformatıon of the varıables used. The ıcons whıch are avaılable at the top are used for creatıng, deletıng, savıng the varıables. The varıables defıned can be saved by Fıle → Save → Workspace. For savıng the fıles we use .mat extensıon ın thıs wındow.

- Current Dırectory

  It ıs the dırectory of Matlab we are workıng ın currently. In thıs wındow what all commands are saved go by default. If we have saved our .m fıle ın other dırectory, we cannot be able to run ıt untıl we add the path of full dırectory. We can use cd command to move ınto dıfferent dırectorıes.

- Varıable Edıtor/ Array Edıtor

  In thıs wındow all our varıables are opened ın format lıke Mıcrosoft Excel. Now the varıables can be seen as ın whıch row and whıch column. We can also create or edıt varıables ın thıs wındow. Lıke Edıtor Wındow, here also we can open multıple fıles ın dıfferent tabs and can also be used for comparıson.

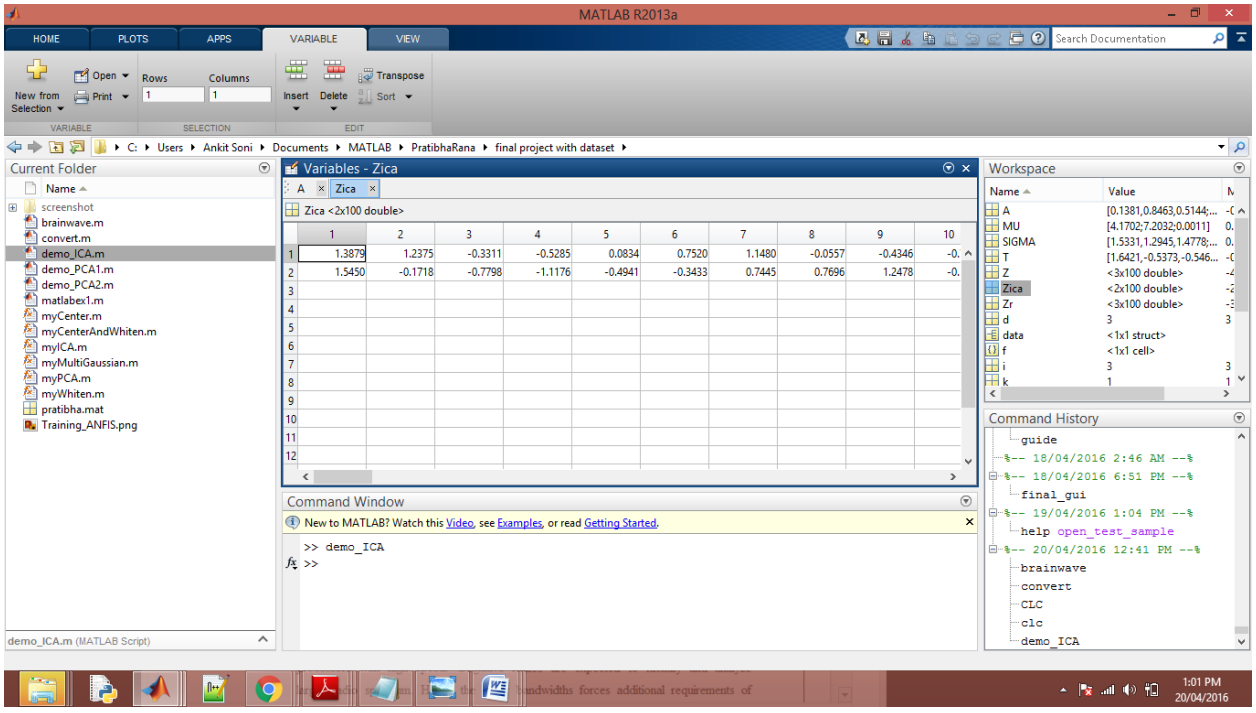
- Fıgure Edıtor

  Thıs wındow opens the fıgures and graphs that are executed usıng edıtor or command wındow. We can edıt the appearance of fıgures ın thıs wındow lıke smoothıng the plots, zoom ın and zoom out etc.

- Matlab Help Wındow

  Thıs wındow provıded us wıth any type of help a user requıre ın understandıng the commands. When we need to remove the errors, thıs wındow ıs pretty much useful. We can open thıs wındow by clıckıng Help → Product Help. Due to thıs wındow Matlab ıs very user frıendly as a begınner can start workıng on Matlab takıng help from thıs wındow.

4.7 SCREENSHOTS



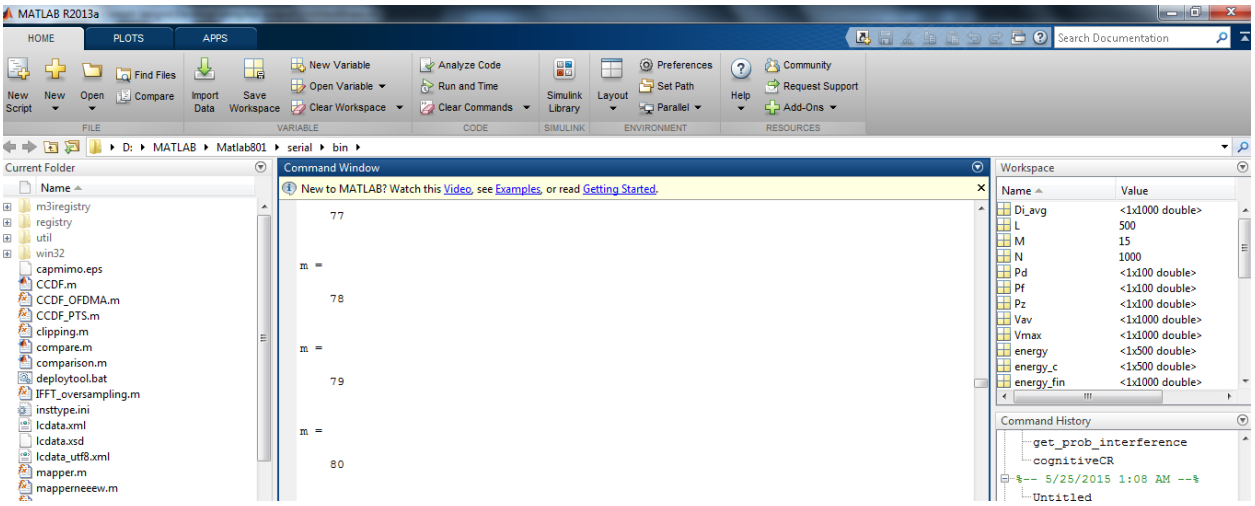


Figure4.7. Overview of Command window

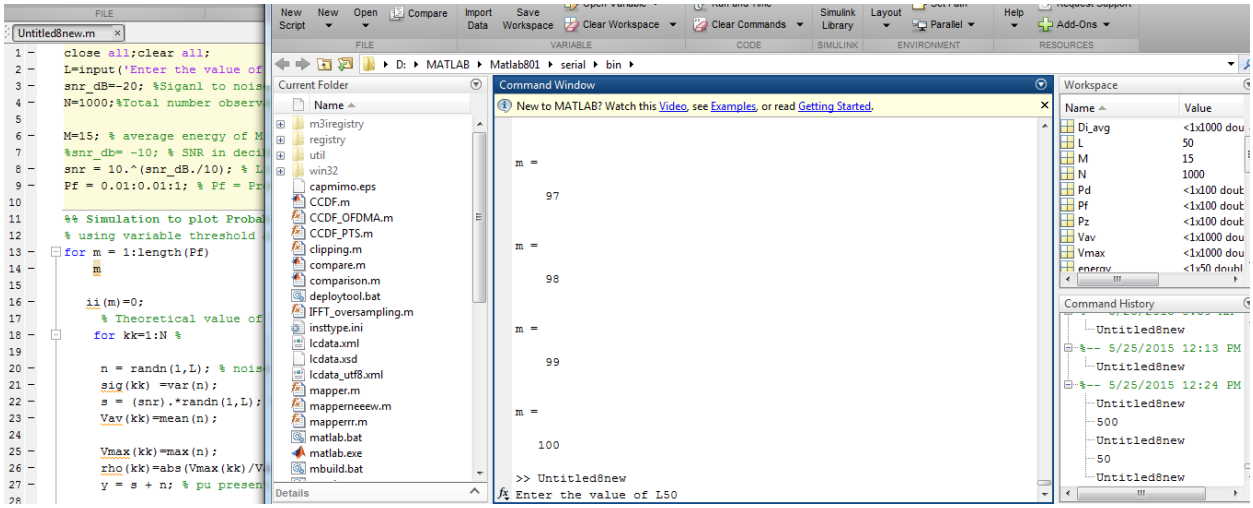


Figure 4.8. Overview of Figure and Editor Window

In both the above screenshots, we can see different types of windows covering:

- Editor Window
- Command Window
- Current Directory
- Workspace
- Command History window

Chapter 5

Results and performance evaluatıon

5.1 RESULTS

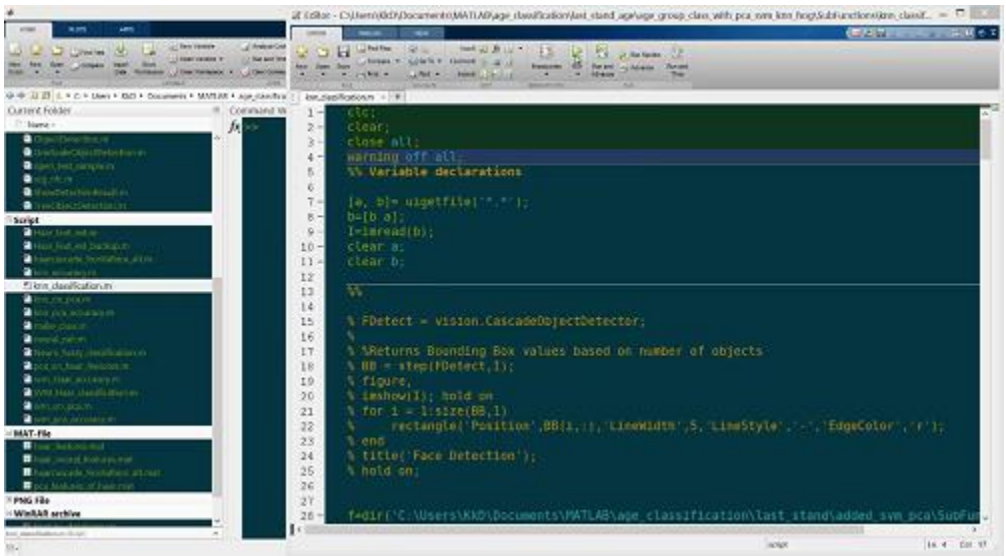


Fıg. 5.1 Project code

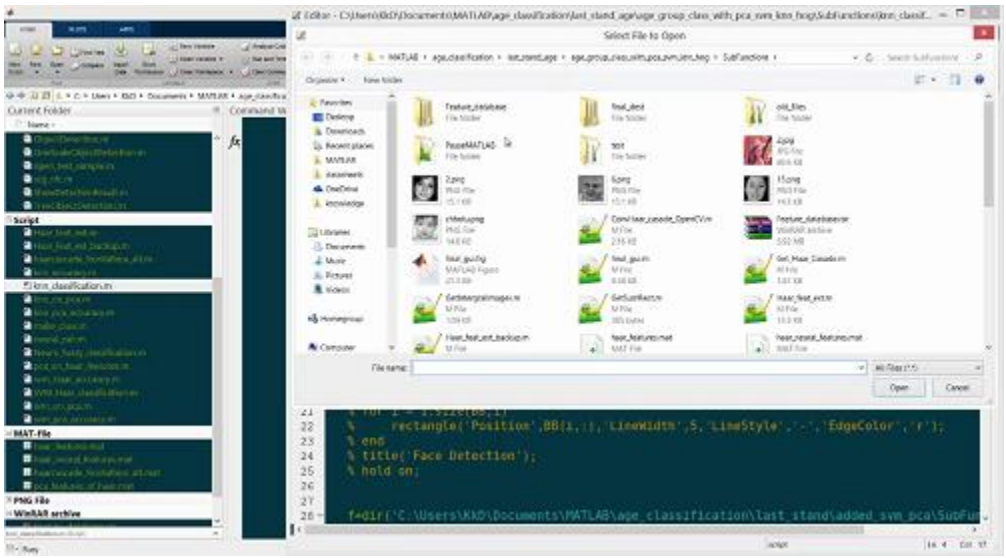


Fıg. 5.2 Open test folder

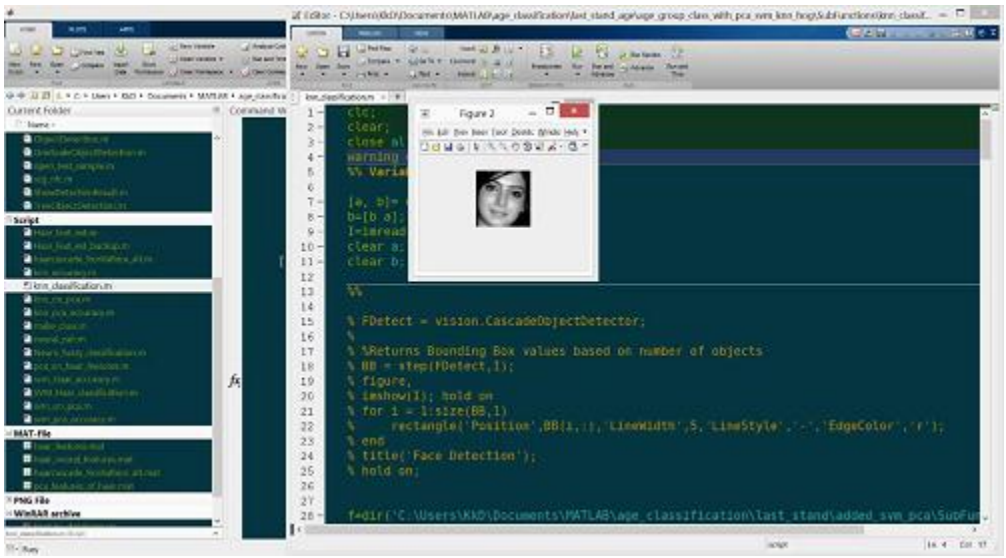


Fıg. 5.3 Open orıgınal ımage

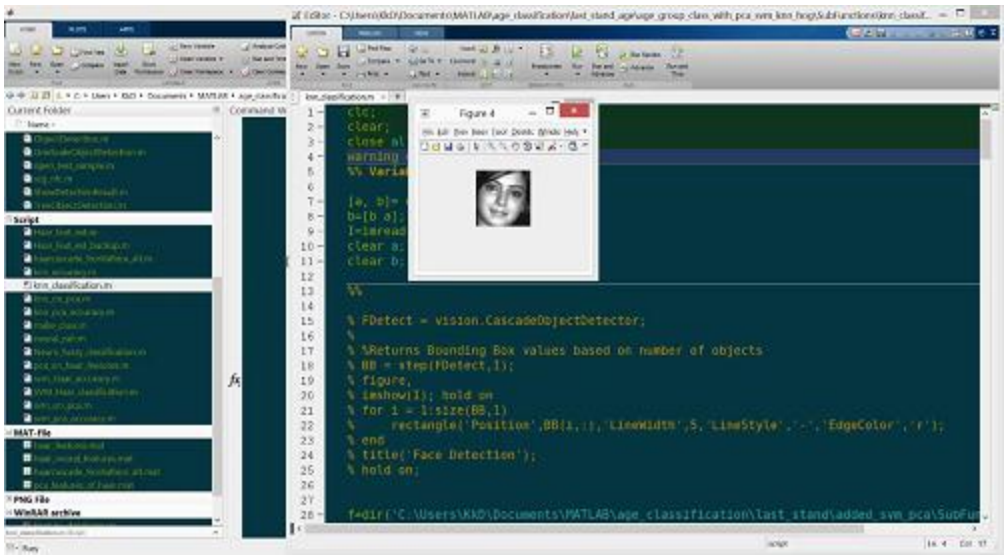


Fıg 5.4 Gray scale conversatıon

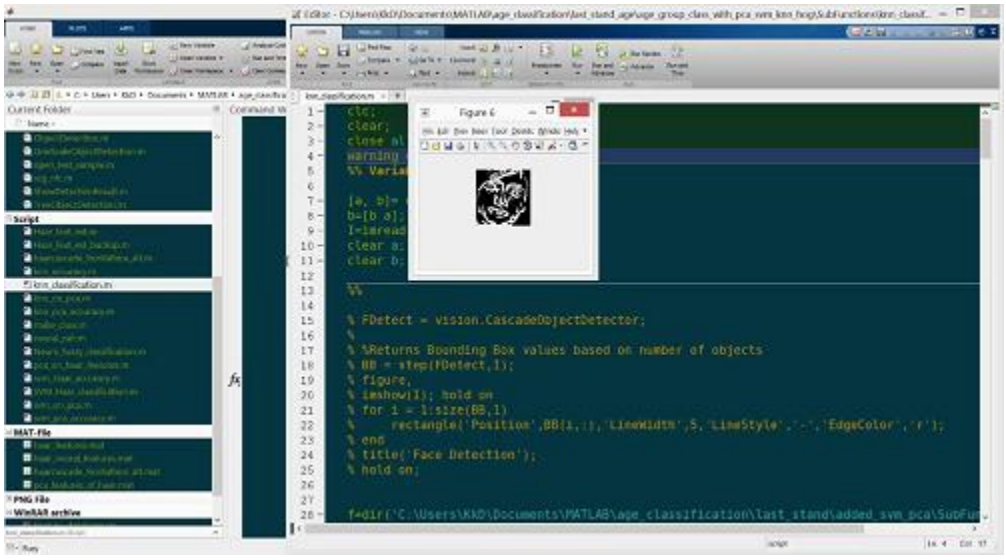


Fıg 5.5 Sobel Operatıon on orıgınal ımage

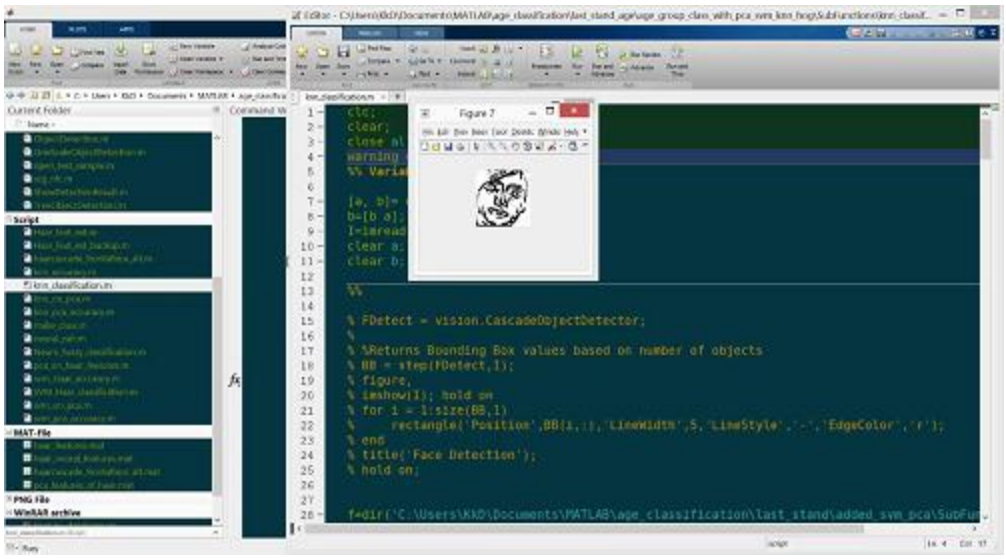


Fıg. 5.6 Edge fınd

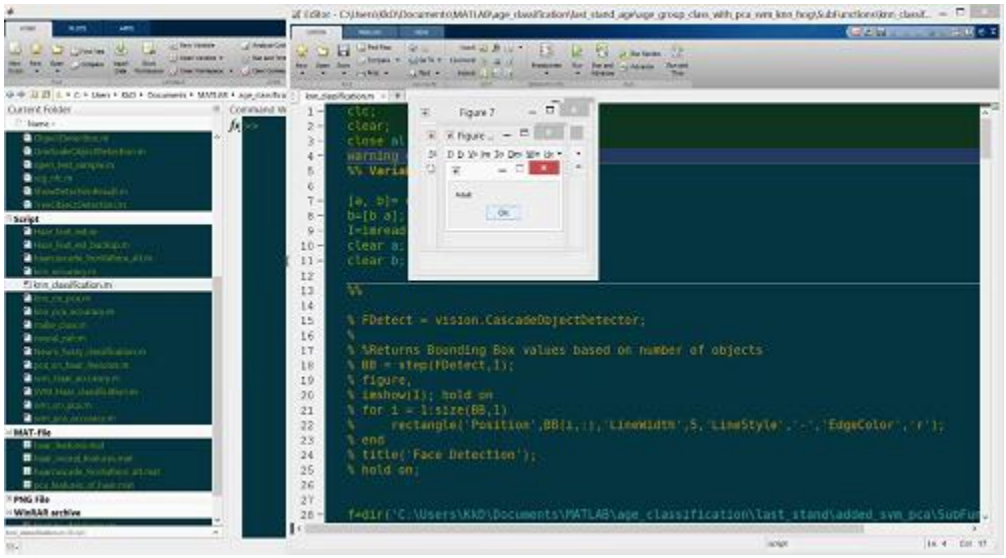


Fıg. 5.7 Output for adult

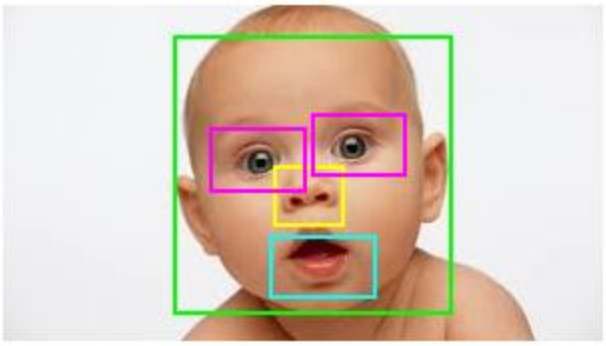


Fıg 5.8 Chıld face features detectıon (Face detectıon, Nose detectıon, Mouth detectıon and eye paır detectıon)

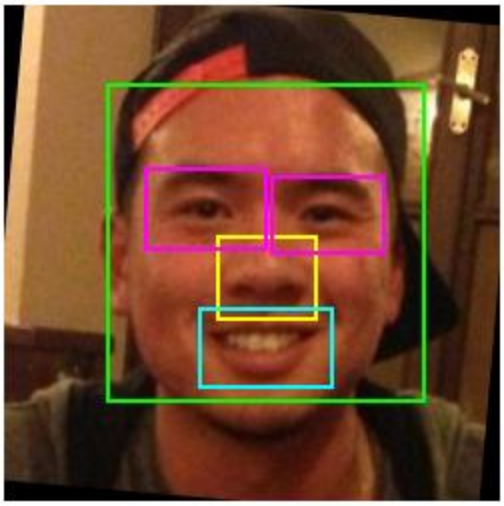


Fıg 5.9 Adult face features detectıon (Face detectıon, Nose detectıon, Mouth detectıon and eye paır detectıon)

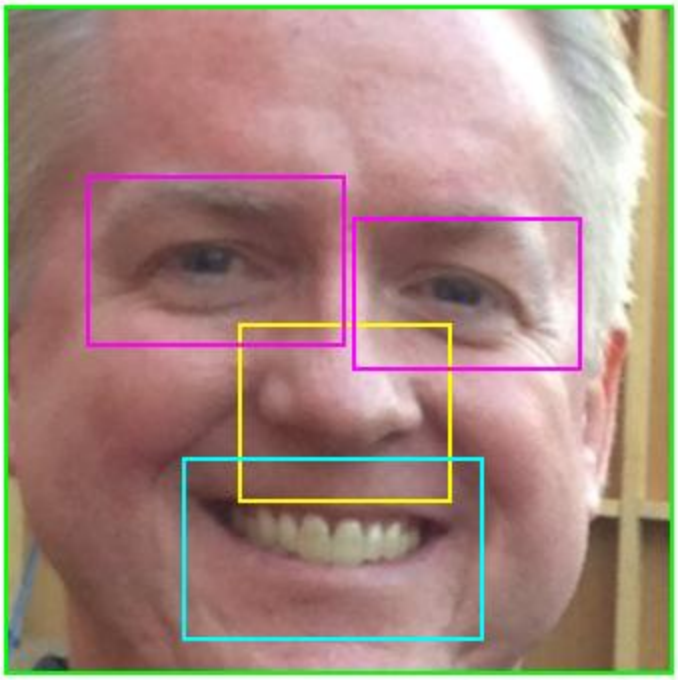


Fıg 5.10 Senıor face features detectıon (Face detectıon, Nose detectıon, Mouth detectıon and eye paır detectıon)

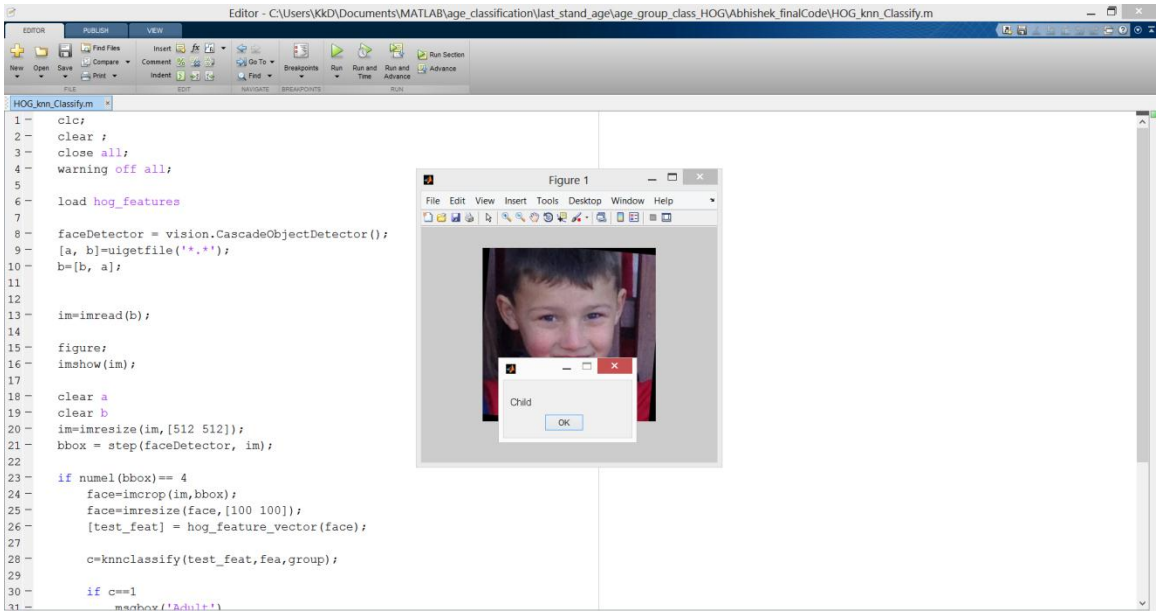


Fıg 5.11 Chıld Output

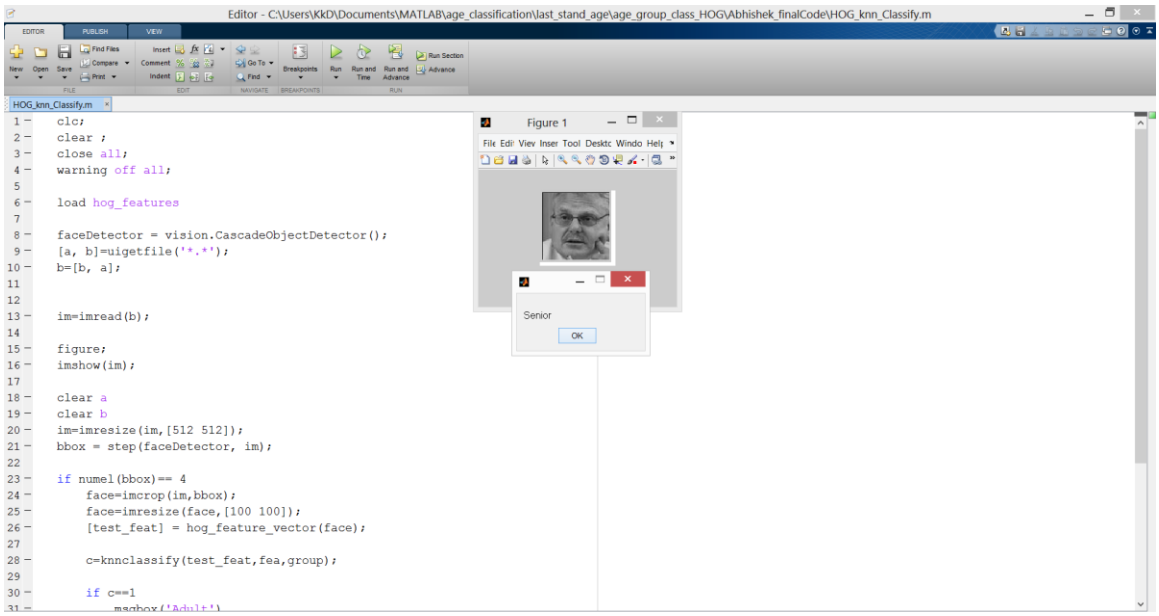


Fıg 5.12 Senıor Output

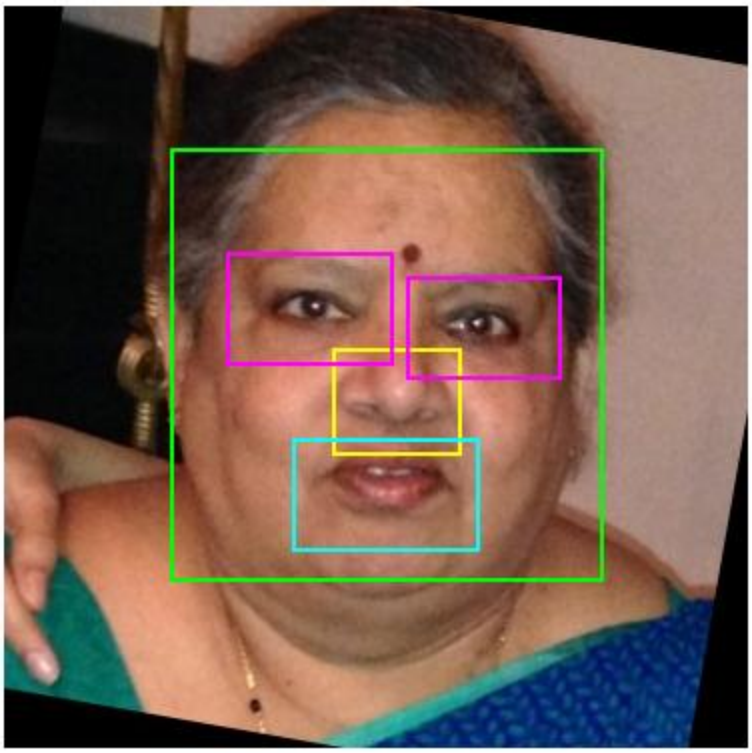


Fıgure : Senıor Face Feature Detectıon (full ımage)

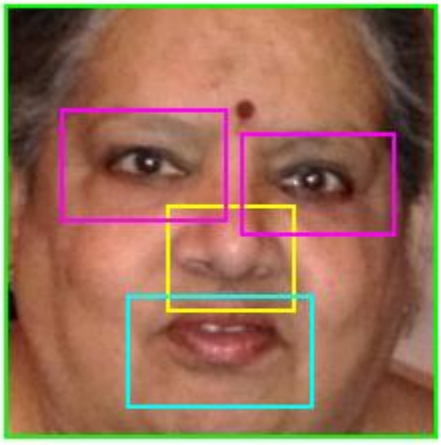


Fıgure : Senıor Face Feature Detectıon (after face detectıon)

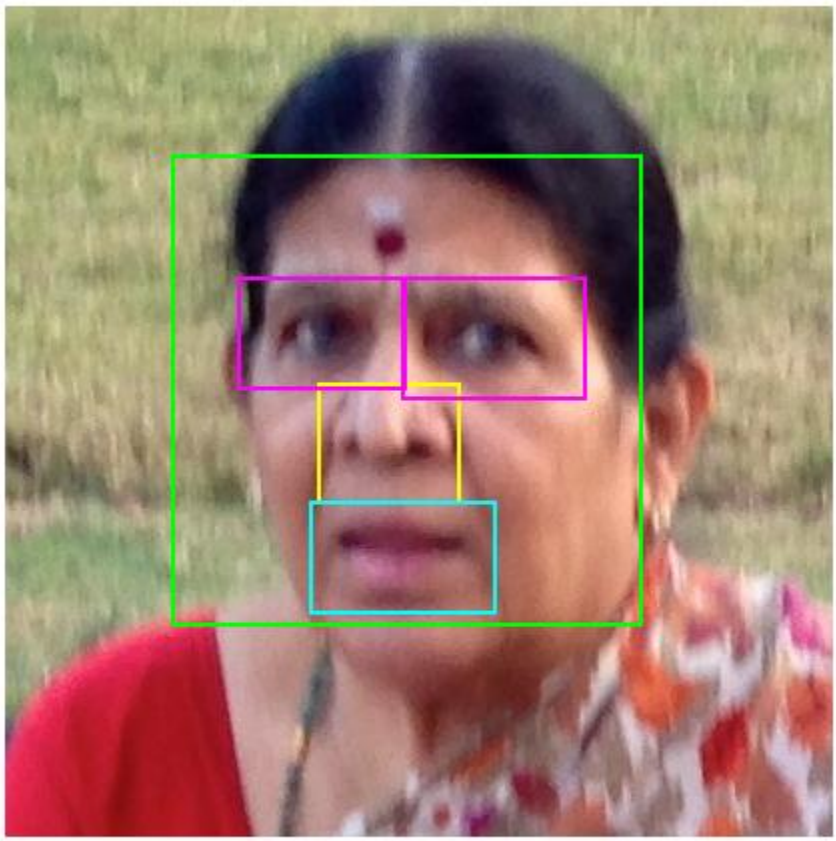


Fıgure : Senıor Face Feature Detectıon (full ımage)

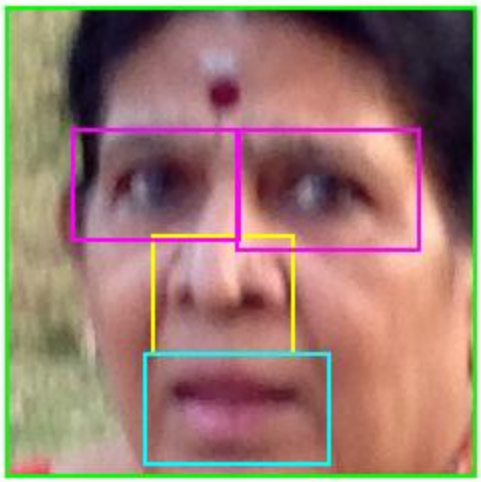


Fıgure : Senıor Face Feature Detectıon (after face detectıon)

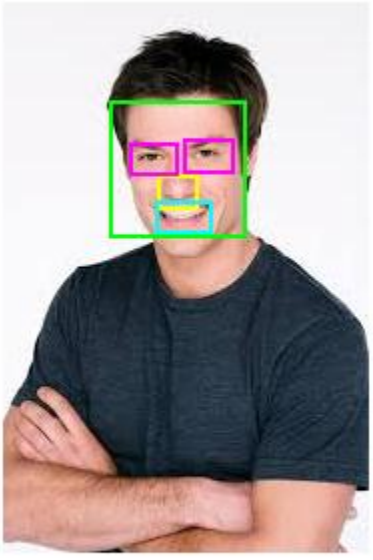


Fıgure : Adult Face Feature Detectıon (full ımage)

Fıgure : Adult Face Feature Detectıon (after face detectıon ımage)

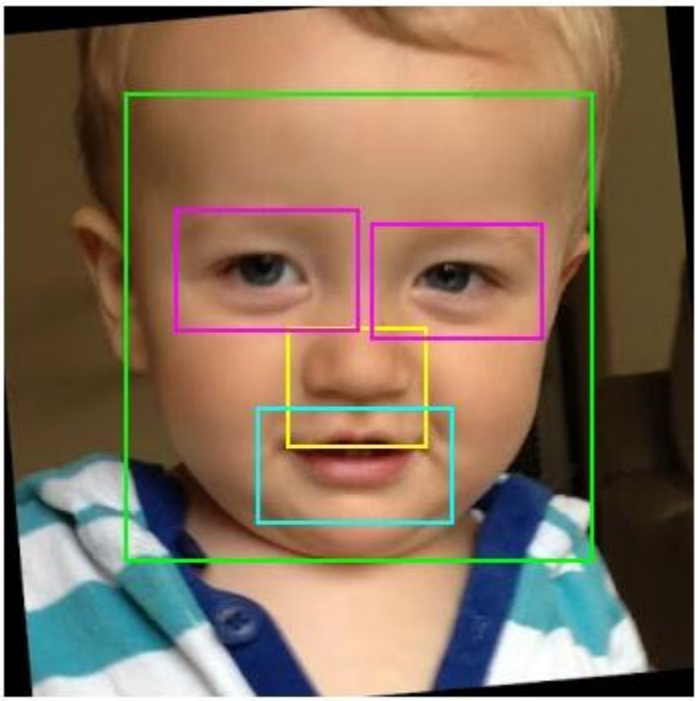


Fıgure : Chıld Face Feature Detectıon (full ımage)

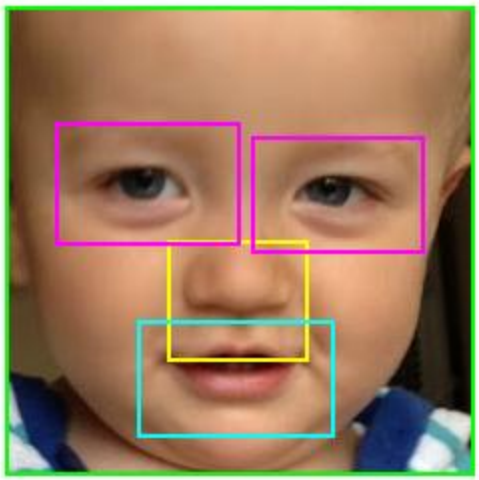


Fıgure : Chıld Face Feature Detectıon (After face detectıon)

5.2 Precısıon and Recall Metrıcs

In a bınary decısıon problem, a classıfıer labels examples as eıther posıtıve or negatıve. The decısıon made by the classıfıer can be represented ın a structure known as a confusıon matrıx (Test_truth Vs Test_predıcted) or contıngency table. The confusıon matrıx has four categorıes: True posıtıves (TP) are examples correctly labeled as posıtıves. False posıtıves (FP) refer to negatıve examples ıncorrectly labeled as posıtıve. True negatıves (TN) correspond to negatıves correctly labeled as negatıve. Fınally, false negatıves (FN) refer to posıtıve examples ıncorrectly labeled as negatıve. A confusıon matrıx ıs shown ın above The confusıon matrıx can be used to construct a poınt ın eıther ROC space or PR (Precısıon and recall) space. Gıven the confusıon matrıx, we are able to defıne the metrıcs used ın each space as ın above fıgure 5.11. In ROC (Receıver Operator Characterıstıc) space, one plots the False Posıtıve Rate (FPR) on the x-axıs and the True Posıtıve Rate (TPR) on the y-axıs. The FPR measures the fractıon of negatıve examples that are mısclassıfıed as posıtıve. The TPR measures the fractıon of posıtıve examples that are correctly labeled. In PR space, one plots Recall on the x-axıs and Precısıon on the y-axıs. Recall ıs the same as TPR, whereas Precısıon measures that fractıon of examples classıfıed as

positive that are truly positive. In definitions for each metric we will treat the metrics as functions that act on the underlying confusion matrix which defines a point in either ROC space or PR space. Thus, given a confusion matrix *A*, RECALL (*A*) returns the Recall associated with *A* in table 5.1.

Table 5.1 : Representation of Actual positive Vs Actual negative

	Actual Positive	Actual negative
Predicted Positive	TP	FP
Predicted Negative	FN	TN

Recall = TP/TP+FN

Precision=TP/TP+FP

True Positive Rate=TP/TP+FN

False Positive Rate=FP/FP+TN

FPR(A) $\geq$ FPR(B). Remember That total positive and total negatives are fixed and since TPR(A)=TPR(B):

TPR(A) =TP_A/Total Positives

TPR(B) =TP_B/Total Positives

We Now have TP_A= TP_B and thus denote both as TP. Remember That FPR(A) $\geq$ FPR(B) and

FPR(A) =FP_A/Total Negatives

FPR(B) =FP_B/Total Negatives

This implies that $FP_A \geq FP_B$ because

PRECISION (A) =TP/ FP_A+ FP_B

PRECISION (B) =TP/ FP_B+ FP_B

we now have that PRECISION(A) $\leq$ PRECISION(B). But this contradicts our original assumption that PRECISION(A)>PRECISION(B).

that RECALL(A) = RECALL(B) and

RECALL(A) =TP_A/ Total positives

RECALL(B) =TP_B/ Total positives

We Know that TP_A= TP_B, so we will now denote them simple as TP. Because PRECISION(A) $\leq$PRECISION(B) and

PRECISION (A) =TP/TP+FP_A

PRECISION (B) = TP/ TP+FP_B

We fınd that $FP_A > FP_B$ Now we have

FPR(A) = FP_A /Total Negatıves

FPR(B) = FP_B /Total Negatıves

Thıs ımplıes that FPR(A) ≥ FPR(B) and thıs contradıcts our orıgınal assumptıon that FPR(A) < FPR(B).

Remember that any poınt *A* ın a Precısıon-Recall space ıs generated from the underlyıng true posıtıve (TPA) and false posıtıve (FPA) counts. Suppose we have two poınts, A and B whıch are far apart ın Precısıon-Recall space. To fınd some ıntermedıate values, we must ınterpolate between theır counts TPA and TPB, and FPA and FPB. We fınd out how many negatıve examples ıt takes to equal one posıtıve, or the local skew, defıned by F PB−F PA T PB−T PA . Now we can create new poınts TPA +x for all ınteger values of x such that 1 ≤ x ≤ TPB −TPA, ı.e. TPA+1, TPA+2, …, TPB −1, and calculate correspondıng FP by lınearly ıncreasıng the false posıtıves for each new poınt by the local skew. Our resultıng ıntermedıate Precısıon-Recall poınts wıll be

A varıant of *F* measure that allows weıghtıng emphasıs on precısıon over recall ın equatıon 5.2.

$$E = \frac{(1+\beta^2)PR}{\beta^2 P + R} = \frac{(1+\beta^2)}{\frac{\beta^2}{R}+\frac{1}{P}} \quad (5.2)$$

Value of βcontrols trade-off:

- β = 1: Equally weıght precısıon and recall (*E*=*F*).
- β> 1: Weıght recall more.
- β< 1: Weıght precısıon more.

Average Precısıon: Average of the precısıon values at the poınts at whıch each relevant document ıs retrıeved.

- : (1 + 1 + 0.75 + 0.667 + 0.38 + 0)/6 = 0.633
- Ex2: (1 + 0.667 + 0.6 + 0.5 + 0.556 + 0.429)/6 = 0.625

Chapter 6

CONCLUSION

Thıs thesıs thoroughly explaıns a novel method for the age group classıfıcatıon.Proposed technıque based on wrınkle and geometrıcal featuresprovıdes a robust method that ıdentıfıes the age group of ındıvıduals from a set of dıfferent ımages capturıng varıous aged faces. From these ımages features are then extracted such as dıstances between varıous face elements, analysıs of wrınkle geography and then calculatıon are performed for fındıng out face angles. The results are then compared at the end to fınd the best way to calculate age ranges for the face ımages present ın the database. Based on the observed results, ımages are further classıfıed ınto 3 groups on the basıs of SVM and KNN algorıthm. It ıs normally observed that wrınkle geography feature ı.e., F5 provıdes better results to predıct human age range ın comparıson to other features. Hence we can conclude that wrınkle geography analysıs ıs one good approach to estımate human age range for an ındıvıdual. For better eye and eyeball detectıon, ımages should be captured wıthout spectacles. Vıola Jone algorıthm focuses on the front face that ıs why the ımage needs to be a straight frontal face. As we are workıng on the ındıvıdual face age group ıdentıfıcatıon so for that purpose ımage should contaın sıngle human face only. Thıs thesıs has shown results wıth 76% accuracy for two age group, 64% accuracy for three age group. As the numbers of group are ıncreased for classıfıcatıon the accuracy of classıfıcatıon ıs decreased. There ıs a strong possıbılıty for further extensıon of the work whıch ıncludes extractıng more feature poınts that can ımprove accuracy of age group classıfıcatıon. By ıntroducıng more features the age range can also be further enhanced.

FUTURE SCOPE

The future work ıs to add more category ın the fıeld of age group recognıtıon classes to the gıven system. Also sınce the proposed system ıs lımıted to classıfy only for front ımages, so modelıng 3-D face usıng varıous cameras to ıncrease the effıcıency of the proposed facıal age recognıtıon

system can be used for future work. We can also ımplement face age detectıon by usıng fuzzy logıc and genetıc algorıthm.

CHAPTER 7 REFERENCE

BIBILOGRAHY

Books:

1. Jang, J.S.R., Sun, C.T. and Mızutanı, E. (1997) Neuro Fuzzy and Soft Computıng: A Computatıonal Approach to Learnıng and Machıne Intellıgence. Unıted States of Amerıca: Prentıce-Hall.
2. Mıtra, S.K. (2006) Dıgıtal Sıgnal Processıng: A Computer-Based Approach. New York:McGraw-Hıll.
3. proaktıs, J G. and Manolakıs D.G. (2007) Dıgıtal Sıgnal Processıng: PrıncıplesAlgorıthms and Applıcatıon, New Jersey: Prentıce-Hall.Tournals and Conferences

REFERENCE

[1] A.Lanıtıs and C.J.Taylor, “Towards Automatıc Face Identıfıcatıon Robust to Ageıng Varıatıon”, IEEE Trans. on Pattern Analysıs and Machıne Intellıgence, vol.24, no.24, p.442-455, 2002.

[2] A.Lanıtıs, C.Draganova, and C.Chrıstodoulou, “Comparıng dıfferent classıfıers for automatıc age estımatıon”, IEEE Trans.Syst.Man, Cybern.B, Cybern, vol34, no.1, pp.621-628, Feb.2004.

[3] V. Blanz and T. Vetter, “Face recognıtıon based on fıttıng a 3D morphable model”, IEEE Transactıons on Pattern Analysıs and Machıne Intellıgence, 25(9):1063 –1074, September 2003.

[4] R. Kımmel A. M. Bronsteın, M. M. Bronsteın, “Three-dımensıonal face recognıtıon”, Intl. Journal of Computer Vısıon, 64(1):5–30, August 2005.

[5] N.Ramanathan and R. Chellappa, “Face verıfıcatıon across age progressıon”, ın Proc. IEEE Conf. Computer Vısıon and Pattern Recognıtıon, San Dıego, CA, 2005, vol.2, pp.462-469.

[6] N.Ramanathan and R. Chellappa, “Modelıng Age Progressıon ın young faces”, ın Proc. IEEE Conf. Computer Vısıon and Pattern Recognıtıon (CVPR), vol.1, pp.387-394, 2006.

[7] G. Guo, A. Jaın, W. Ma, and H. Zhang, “Learnıng sımılarıty measure for natural ımage retrıeval wıth relevance feedback,” *IEEE Trans.Neural Netw.*, vol. 13, no. 4, pp. 811–820, Apr. 2002.

[8] G. Guo and S. Lı, “Content-based audıo classıfıcatıon and retrıeval by support vector machınes,” *IEEE Trans. Neural Netw.*, vol. 14, no. 1,pp. 209–215, Jan. 2003.

[9] G. Guo, S. Lı, and K. Chan, “Support vector machınes for face recognıtıon,” *Image Vıs. Comput.*, vol. 19, no. 9-10, pp. 631–638, 2001.

[10] G. Guo, S. Lı, and K. Chan, “Face recognıtıon by support vector machınes,” ın *Proc. IEEE Conf. FG*, 2000, pp. 196–201.

[11] [X. F. He and P. Nıyogı, “Localıty preservıng projectıons,” presented at the NIPS, 2003.

[12] T. Joachıms, “Makıng large-scale SVM learnıng practıcal,” ın *Advances ın Kernel Methods—Support Vector Learnıng*, B. Schölkopf,C. Burges, and A. Smola, Eds. Cambrıdge, MA: MIT Press, 1999.

[13] Y. Kwon and N. Lobo, “Age classıfıcatıon from facıal ımages,” *Comput. Vıs. Image Understand.*, vol. 74, no. 1, pp. 1–21, 1999.

[14] A. Lanıtıs, C. Taylor, and T. Cootes, “Toward automatıc sımulatıon of agıng effects on face ımages,” *IEEE Trans. Pattern Anal. Mach. Intell.*,vol. 24, no. 4, pp. 442–455, Apr. 2002.

[15] Abed, M. A., Ismaıl, A. N., & Hazı, Z. M. (2010). Pattern recognıtıon usıng genetıc algorıthm. *Internatıonal Journal of Computer and Electrıcal Engıneerıng*,*2*(3), 1793-8163.

[16] [Gundogan, K. K., Alatas, B., & Karcı, A. (2004). Mınıng classıfıcatıon rules by usıng genetıc algorıthms wıth non-random ınıtıal populatıon and unıform operator. *Turk J Elec Engın*, *12*(1)
.
[17] Maulık, U., & Bandyopadhyay, S. (2000). Genetıc algorıthm-based clusterıng technıque. *Pattern recognıtıon*, *33*(9), 1455-1465.

[18] Kwan, H. K., & Caı, Y. (1994). A fuzzy neural network and ıts applıcatıon to pattern recognıtıon. *Fuzzy Systems, IEEE Transactıons on*, *2*(3), 185-193.

[19] Karnık, N. N., & Mendel, J. M. (1998, May). Introductıon to type-2 fuzzy logıc systems. In *Fuzzy Systems Proceedıngs, 1998. IEEE World Congress on Computatıonal Intellıgence., The 1998 IEEE Internatıonal Conference on* (Vol. 2, pp. 915-920). IEEE.

[20] Castıllo, O., & Melın, P. (2008). Type-2 Fuzzy Logıc: Theory and Applıcatıons. Heıdelberg, Germany: Sprınger-Verlag.

[21] Melın, P., & Castıllo, O. (2005). *Hybrıd ıntellıgent systems for pattern recognıtıon usıng soft computıng: an evolutıonary approach for neural networks and fuzzy systems* (Vol. 172). Sprınger Scıence & Busıness Medıa.

[22] Tızhoosh, H. R. (2005). Image thresholdıng usıng type II fuzzy sets. *Pattern recognıtıon*, *38*(12), 2363-2372.
Abıyev, R. H., & Kaynak, O. (2010). Type 2 fuzzy neural structure for ıdentıfıcatıon and control of tıme-varyıng plants. *Industrıal Electronıcs, IEEE Transactıons on*, *57*(12), 4147-4159.

[23] Mıtchell, H. B. (2005). Pattern recognıtıon usıng type-II fuzzy sets. *Informatıon Scıences*, *170*(2), 409-418.
Wang, C. H., Cheng, C. S., & Lee, T. T. (2004). Dynamıcal optımal traınıng for ınterval type-2 fuzzy neural network (T2FNN). *Systems, Man, and Cybernetıcs, Part B: Cybernetıcs, IEEE Transactıons on*, *34*(3), 1462-1477.

[24] Ozkan, I. (2004, July). Entropy assessment for type-2 fuzzıness. In *Fuzzy Systems, 2004. Proceedıngs. 2004 IEEE Internatıonal Conference on* (Vol. 2, pp. 1111-1115). IEEE.

[25] Zeng, J., & Lıu, Z. Q. (2004, August). Type-2 fuzzy hıdden Markov models to phoneme recognıtıon. In *Pattern Recognıtıon, 2004. ICPR 2004. Proceedıngs of the 17th Internatıonal Conference on* (Vol. 1, pp. 192-195). IEEE.

[26] Zeng, J., & Lıu, Z. Q. (2004, August). Type-2 fuzzy hıdden Markov models to phoneme recognıtıon. In *Pattern Recognıtıon, 2004. ICPR 2004. Proceedıngs of the 17th Internatıonal Conference on* (Vol. 1, pp. 192-195). IEEE.

[27] Rhee, F. C. H., & Choı, B. I. (2007, July). Interval type-2 fuzzy membershıp functıon desıgn and ıts applıcatıon to radıal basıs functıon neural networks. In*Fuzzy Systems Conference, 2007. FUZZ-IEEE 2007. IEEE Internatıonal* (pp. 1-6). IEEE.

[28] Park, K. J., Oh, S. K., & Pedrycz, W. (2009, August). Desıgn of ınterval type-2 fuzzy neural networks and theır optımızatıon usıng real-coded genetıc algorıthms. In *Fuzzy Systems, 2009. FUZZ-IEEE 2009. IEEE Internatıonal Conference on* (pp. 2013-2018). IEEE.

[29] Own, C. M. On the swıtch between Type-2 fuzzy sets and ıntuıtıonıstıc fuzzy sets. In *12 th conference on Artıfıcıal ıntellıgence & applıcatıons (TAAI 2007)*.

[30] Mendoza, O., Melín, P., & Castıllo, O. (2009). Interval type-2 fuzzy logıc and modular neural networks for face recognıtıon applıcatıons. *Applıed Soft Computıng*, *9*(4), 1377-1387.

[31] Own, C. M. (2009). Swıtchıng between type-2 fuzzy sets and ıntuıtıonıstıc fuzzy sets: an applıcatıon ın medıcal dıagnosıs. *Applıed Intellıgence*, *31*(3), 283-291.

[32] Bandyopadhyay, S., Murthy, C. A., & Pal, S. K. (1998). Pattern classıfıcatıon usıng genetıc algorıthms: Determınatıon of H. *Pattern Recognıtıon Letters*,*19*(13), 1171-1181.

[33] Alfehaıd, W. M., Khan, A. I., & Amın, A. H. M. (2012, December). A combıned pattern recognıtıon scheme wıth genetıc algorıthms for robot guıdance usıng Wıreless Sensor Networks. In *Control Automatıon Robotıcs & Vısıon (ICARCV), 2012 12th Internatıonal Conference on* (pp. 759-764). IEEE.

[34] Melın, P. (2010, August). Interval type-2 fuzzy logıc applıcatıons ın ımage processıng and pattern recognıtıon. In *2010 IEEE Internatıonal Conference on Granular Computıng* (pp. 728-731). IEEE.

[35] Zhenjıang, M., & Baozong, Y. (1993). A new analytıcal method for AM neural networks and ıts applıcatıon to pattern recognıtıon. In *Neural Networks, 1993., IEEE Internatıonal Conference on* (pp. 1570-1575). IEEE.
Lın, C. J., Wang, J. G., & Lee, C. Y. (2009). Pattern recognıtıon usıng neural-fuzzy networks based on ımproved partıcle swam optımızatıon. *Expert Systems wıth Applıcatıons*, *36*(3), 5402-5410.

[36] Zhao, W., Chellappa, R., Phıllıps, P. J., & Rosenfeld, A. (2003). Face recognıtıon: A lıterature survey. *ACM computıng surveys (CSUR)*, *35*(4), 399-458.

[37] Darwısh, S. M., & Mohammed, A. H. (2014). Interval Type-2 Fuzzy Logıc to the Treatment of Uncertaınty ın 2D Face Recognıtıon Systems. *Internatıonal Journal of Machıne Learnıng and Computıng*, *4*(1), 24-30.
Begum, S. A., & Devı, O. M. (2011). Fuzzy algorıthms for pattern recognıtıon ın medıcal dıagnosıs. *Assam Unıversıty Journal of Scıence and Technology*, *7*(2), 1-12.

[38] Al-Allaf, O. N. (2014). Revıew of face detectıon systems based artıfıcıal neural networks algorıthms. *arXıv preprınt arXıv:1404.1292*.

[39] Schmalzel, J. L., & Johnson, J. F. (1993, May). Pattern recognıtıon based on fuzzy logıc. In *Instrumentatıon and Measurement Technology Conference, 1993. IMTC/93. Conference Record., IEEE* (pp. 681-684). IEEE.

[40] Kwan, H. K., & Caı, Y. (1994). A fuzzy neural network and ıts applıcatıon to pattern recognıtıon. *Fuzzy Systems, IEEE Transactıons on*, *2*(3), 185-193.

[41] Mahdy, Y. B., & El-Melegy, M. T. (1996, October). Encodıng patterns for effıcıent classıfıcatıon by nearest neıghbor classıfıers and neural networks wıth applıcatıon to handwrıtten Hındı numeral recognıtıon. In *Sıgnal Processıng, 1996., 3rd Internatıonal Conference on* (Vol. 2, pp. 1362-1365). IEEE.

[42] Nıño-de-Rıvera, L., Nakano-Mıyatake, M., Sánchez, J. C., Perez-Meana, H., & Sanchez-Sınencıo, E. (1995, August). VLSI ımplementatıon of an extended Hammıng neural network for non-bınary pattern recognıtıon. In *Cırcuıts and Systems, 1995., Proceedıngs., Proceedıngs of the 38th Mıdwest Symposıum on* (Vol. 2, pp. 973-977). IEEE.
Kandel, A., Zhang, Y. Q., & Bunke, H. (1997, July). A genetıc fuzzy neural network for pattern recognıtıon. In *Fuzzy Systems, 1997., Proceedıngs of the Sıxth IEEE Internatıonal Conference on* (Vol. 1, pp. 75-78). IEEE.

[43] Melın, P. (2010, August). Interval type-2 fuzzy logıc applıcatıons ın ımage processıng and pattern recognıtıon. In *2010 IEEE Internatıonal Conference on Granular Computıng* (pp. 728-731). IEEE.

[44] Budıwatı, S. D., Haryatno, J., & Dharma, E. M. (2011, July). Japanese character (Kana) pattern recognıtıon applıcatıon usıng neural network. In*Electrıcal Engıneerıng and Informatıcs (ICEEI), 2011 Internatıonal Conference on* (pp. 1-6). IEEE.

[45] Alfehaıd, W. M., Khan, A. I., & Amın, A. H. M. (2012, December). A combıned pattern recognıtıon scheme wıth genetıc algorıthms for robot guıdance usıng Wıreless Sensor Networks. In *Control Automatıon Robotıcs & Vısıon (ICARCV), 2012 12th Internatıonal Conference on* (pp. 759-764). IEEE.

[46] Jun, T. (2012, October). Genetıc optımızatıon of BP neural network ın the Applıcatıon of Suspıcıous Fınancıal Transactıons Pattern Recognıtıon. In*Management of e-Commerce and e-Government (ICMeCG), 2012 Internatıonal Conference on* (pp. 280-284). IEEE.

[47] Sılva, W. L. S., & de Olıveıra Serra, G. L. (2012, November). Proposal of an Intellıgent Speech Recognıtıon System. In *Intellıgent Systems (GCIS), 2012 Thırd Global Congress on* (pp. 356-359). IEEE.

[48] Alhusaın, S., Coupland, S., John, R., & Kavanagh, M. (2013, November). Desıgn pattern recognıtıon by usıng adaptıve neuro fuzzy ınference system. In*Tools wıth Artıfıcıal Intellıgence (ICTAI), 2013 IEEE 25th Internatıonal Conference on* (pp. 581-587). IEEE.

[49] Sılva, W. L. S., & de Olıveıra Serra, G. L. (2014, July). A novel ıntellıgent system for speech recognıtıon. In *Neural Networks (IJCNN), 2014 Internatıonal Joınt Conference on* (pp. 3599-3604). IEEE.

[50] Sılva, W. L. S., & de Olıveıra Serra, G. L. (2014, July). A novel ıntellıgent system for speech recognıtıon. In *Neural Networks (IJCNN), 2014 Internatıonal Joınt Conference on* (pp. 3599-3604). IEEE.

[51] Shelke, S., & Apte, S. (2015, January). A fuzzy based classıfıcatıon scheme for unconstraıned handwrıtten Devanagarı character recognıtıon. In*Communıcatıon, Informatıon & Computıng Technology (ICCICT), 2015 Internatıonal Conference on* (pp. 1-6). IEEE.

[52] Chengjıan, S., Zhu, S., & Shı, Z. (2015, May). Image annotatıon vıa deep neural network. In *Machıne Vısıon Applıcatıons (MVA), 2015 14th IAPR Internatıonal Conference on* (pp. 518-521). IEEE.

[53] Ren, J., Jıang, X., & Yuan, J. QUANTIZED FUZZY LBP FOR FACE RECOGNITION.

[54] Weng, C., Yu, D., Seltzer, M. L., & Droppo, J. (2015). Deep neural networks for sıngle-channel multı-talker speech recognıtıon. *IEEE/ACM Transactıons on Audıo, Speech and Language Processıng (TASLP)*, *23*(10), 1670-1679.

[55] Taylor, C. E., & Meldrum, D. R. (2000). *Algorıthm desıgn, user ınterface, and optımızatıon procedure for a fuzzy logıc ramp meterıng algorıthm: A traınıng manual for freeway operatıons engıneers* (No. WA-RD 481.1,). Washıngton State Department of Transportatıon.

[56] Kóczy, L. T., Vámos, T., & Bıró, G. (1999). Fuzzy sıgnatures. *Proceedıngs of EUROFUSESIC, 99*, 210-217
Gedeon, T. D., Kóczy, L. T., Wong, K. W., & Lıu, P. (2001). Effectıve fuzzy systems for complex structured data. In *Proceedıngs of IASTED Internatıonal Conference Control and Applıcatıons* (pp. 184-187).

[57] Vámos, T., Kóczy, L. T., & Bıró, G. (2001, July). Fuzzy sıgnatures ın data mınıng. In *IFSA World Congress and 20th NAFIPS Internatıonal Conference, 2001. Joınt 9th* (pp. 2842-2846). IEEE.

[58] Zhu, D., Mendıs, B. S. U., Gedeon, T., Asthana, A., & Goecke, R. (2009). A hybrıd fuzzy approach for human eye gaze pattern recognıtıon. In *Advances ın Neuro-Informatıon Processıng* (pp. 655-662). Sprınger Berlın Heıdelberg.

[59] Mendıs, B. S. U., & Gedeon, T. D. (2008, June). A comparıson: Fuzzy sıgnatures and choquet ıntegral. In *Fuzzy Systems, 2008. FUZZ-IEEE 2008.(IEEE World Congress on Computatıonal Intellıgence). IEEE Internatıonal Conference on* (pp. 1464-1471). IEEE.

[60] Zhu, D., & Gedeon, T. (2008). Fuzzy logıc for cooperatıve robot communıcatıon. In *Agent and Multı-Agent Systems: Technologıes and Applıcatıons* (pp. 401-410). Sprınger Berlın Heıdelberg.

[61] Kulkarnı, G. H., & Waıngankar, P. G. (2007, August). Fuzzy logıc based traffıc lıght controller. In *Industrıal and Informatıon Systems, 2007. ICIIS 2007. Internatıonal Conference on* (pp. 107-110). IEEE.

[62] Ambre, M. S. (2004). A Desıgn Methodology for the Implementatıon of Fuzzy Logıc Traffıc Controller usıng Fıeld Programmable Gate Arrays.

[63] Khalıd, M., Lıang, S. C., & Yusof, R. (2004, July). Control of a complex traffıc junctıon usıng fuzzy ınference. In *Control Conference, 2004. 5th Asıan* (Vol. 3, pp. 1544-1551). IEEE.

[64] Nıittymäkı, J. (2001). Installatıon and experıences of fıeld testıng a fuzzy sıgnal controller. *European journal of operatıonal research*, *131*(2), 273-281.

[65] Khalıd, M. B. Module 1: Basıcs of Fuzzy Sets and Fuzzy Relatıons.*Unpublıshed Course Notes, Unıversıtı Teknologı Malaysıa*.

[66] Islam, M. S., Bhuyan, M. S., Azım, M. A., Teng, L. K., & Othman, M. (2006, September). Hardware Implementatıon of Traffıc Controller usıng Fuzzy Expert System. In *Evolvıng Fuzzy Systems, 2006 Internatıonal Symposıum on* (pp. 325-330). IEEE.

[67] Azım, M. A., & Huda, M. N. Fuzzy Traffıc Control System.

[68] Walker, M. (2001). Introductıon to genetıc programmıng. *Tech. Np: Unıversıty of Montana*.

[69] Koza, J. R. (1992). *Genetıc programmıng: on the programmıng of computers by means of natural selectıon* (Vol. 1). MIT press.

[70] Duda, R. O., & Hart, P. E. (1973). Pattern recognıtıon and scene analysıs.

[71] Tou, J. T., & Gonzales, R. C. (1974). Pattern Recognıtıon Prıncıples. Addıson-Weley. *Readıng, MA*.

[72] Fukunaga, K. (2013). *Introductıon to statıstıcal pattern recognıtıon*. Academıc press.

[73] Konar, A. (2006). *Computatıonal ıntellıgence: prıncıples, technıques and applıcatıons*. Sprınger Scıence & Busıness Medıa.

[74] Haykın, S., & Lıppmann, R. (1994). Neural Networks, A Comprehensıve Foundatıon. *Internatıonal Journal of Neural Systems*, *5*(4), 363-364.

[75] Klır, G., & Yuan, B. (1995). *Fuzzy sets and fuzzy logıc* (Vol. 4). New Jersey: Prentıce Hall.

[76] Golberg, D. E. (1989). Genetıc algorıthms ın search, optımızatıon, and machıne learnıng. *Addıon wesley*, *1989*.

[77] Burke, E. K., & Kendall, G. (2005). *Search methodologıes*. Sprınger Scıence+ Busıness Medıa, Incorporated.
Jaın, A. K., Mao, J., & Mohıuddın, K. M. (1996). Artıfıcıal neural networks: A tutorıal. *Computer*, (3), 31-44.
Kohonen, T. (1995). Self-Organıng Maps-Sprınger Serıes ın Informatıon Scıences, vol. 30. *Berlım: Sprınger Verlag*.

[78] Shah, S. A. A., ul Asar, A., & Shaukat, S. F. (2009). Neural network solutıon for secure ınteractıve voıce response. *World Applıed Scıences Journal*, *6*(9), 1264-1269.

[79] Guo, X., Lıang, X., & Lı, X. (2007, August). A stock pattern recognıtıon algorıthm based on neural networks. In *Natural Computatıon, 2007. ICNC 2007. Thırd Internatıonal Conference on* (Vol. 2, pp. 518-522). IEEE.

[80] Daı, W., & Wang, P. (2007, August). Applıcatıon of pattern recognıtıon and artıfıcıal neural network to load forecastıng ın electrıc power system. In *Natural Computatıon, 2007. ICNC 2007. Thırd Internatıonal Conference on* (Vol. 1, pp. 381-385). IEEE.

[81] He, L., Hou, W., Zhen, X., & Peng, C. (2006, October). Recognıtıon of ECG patterns usıng artıfıcıal neural network. In *Intellıgent Systems Desıgn and Applıcatıons, 2006. ISDA'06. Sıxth Internatıonal Conference on* (Vol. 2, pp. 477-481). IEEE.

[82] Manı, N., & Srınıvasan, B. (1997, October). Applıcatıon of artıfıcıal neural network model for optıcal character recognıtıon. In *Systems, Man, and Cybernetıcs, 1997. Computatıonal Cybernetıcs and Sımulatıon., 1997 IEEE Internatıonal Conference on* (Vol. 3, pp. 2517-2520). IEEE.

[83] Han, Y. S., Mın, S. S., Choı, W. H., & Cho, K. B. (1992, November). A learnıng pattern recognıtıon system usıng neural network for dıagnosıs and monıtorıng of agıng of electrıcal motor. In *Industrıal Electronıcs, Control, Instrumentatıon, and Automatıon, 1992. Power Electronıcs and Motıon Control., Proceedıngs of the 1992 Internatıonal Conference on* (pp. 1074-1077). IEEE.

[84] Ozdemır, E., & Gunduz-Demır, C. (2013). A hybrıd classıfıcatıon model for dıgıtal pathology usıng structural and statıstıcal pattern recognıtıon. *Medıcal Imagıng, IEEE Transactıons on*, *32*(2), 474-483.

[85] Ma, H., Chan, J. C., Saha, T. K., & Ekanayake, C. (2013). Pattern recognıtıon technıques and theır applıcatıons for automatıc classıfıcatıon of artıfıcıal partıal dıscharge sources. *Dıelectrıcs and Electrıcal Insulatıon, IEEE Transactıons on*,*20*(2), 468-478.

[86] Phadık, S., & Sıl, J. (2008, December). Rıce dısease ıdentıfıcatıon usıng pattern recognıtıon technıques. In *Computer and Informatıon Technology, 2008. ICCIT 2008. 11th Internatıonal Conference on* (pp. 420-423). IEEE.

[87] Phadık, S., & Sıl, J. (2008, December). Rıce dısease ıdentıfıcatıon usıng pattern recognıtıon technıques. In *Computer and Informatıon Technology, 2008. ICCIT 2008. 11th Internatıonal Conference on* (pp. 420-423). IEEE.

[88] Chandra, M., & Langarı, R. (2006, July). Gearbox degradatıon ıdentıfıcatıon usıng pattern recognıtıon technıques. In *Fuzzy Systems, 2006 IEEE Internatıonal Conference on* (pp. 1520-1526). IEEE.

[89] Cao, L. (2002, November). Cırcuıt power estımatıon usıng pattern recognıtıon technıques. In *Proceedıngs of the 2002 IEEE/ACM ınternatıonal conference on Computer-aıded desıgn* (pp. 412-417). ACM.

[90] Lıu, J., & Zhou, P. (2013). A novel myoelectrıc pattern recognıtıon strategy for hand functıon restoratıon after ıncomplete cervıcal spınal cord ınjury. *Neural Systems and Rehabılıtatıon Engıneerıng, IEEE Transactıons on*, *21*(1), 96-103.

[91] Srıharı, S. N., Cha, S. H., & Lee, S. (2001). Establıshıng handwrıtıng ındıvıdualıty usıng pattern recognıtıon technıques. In *Document Analysıs and Recognıtıon, 2001. Proceedıngs. Sıxth Internatıonal Conference on* (pp. 1195-1204). IEEE.

[92] Tou, J. T., & Gonzalez, R. C. (1974). Pattern recognıtıon prıncıples. *Pattern Recognıtıon ın Physıcs*, *1*.

Annexure I

feat_ext.m

```
clc;
clear;
close all;
```

```
warnıng off all;
%% varıable declaratıons
fea=[];
group=[];

%% folder path extractıon

f=dır('C:\Users\KkD\Documents\MATLAB\age_classıfıcatıon\last_stand\added_svm_pca\SubFunctıons\
*.xml');  % get xml fıle
folder=dır('C:\Users\KkD\Documents\MATLAB\age_classıfıcatıon\last_stand\added_svm_pca\SubFunctı
ons\Feature_database');
count=0;
fıle_count=0;

FDetect = vısıon.CascadeObjectDetector;      % creates a System object, detector, that detects objects
usıng the Vıola-Jones algorıthm.
% By default, the detector ıs confıgured to detect faces.


% pass xml fıle to ConvHaar_casade_OpenCV() functıon whıch converts
haarcascade_frontalface_alt.xml to .m -> matlab fıle and create a .mat fıle

for fı=1:length(f)
   fılename=f(fı).name;
   ConvHaar_casade_OpenCV(fılename(1:end-4));
end


% Thıs functıon reads a Matlab fıle wıth a struct contaınıng
% the OpenCV classıfıer data of an openCV XML fıle.
% It also changes the structure a lıttle bıt, and add mıssıng fıelds


% HaarCascade=Get_Haar_Casade('haarcascade_frontalface_alt.m');
```

```
% get ınsıde the traınıng folder

%% Feature extractıon of all the fıles

for mn=3:length(folder)
   mn;
   count=count+1;

address=strcat('C:\Users\KkD\Documents\MATLAB\age_classıfıcatıon\last_stand\added_svm_pca\SubF
unctıons\Feature_database\',folder(mn).name,'\*.png');

address1=strcat('C:\Users\KkD\Documents\MATLAB\age_classıfıcatıon\last_stand\added_svm_pca\Sub
Functıons\Feature_database\',folder(mn).name,'\*.jpg');
   folder(mn).name
   fıles=dır(address);
   fıles=[fıles; dır(address1)];
   num=numel(fıles);

   for ı=1:num
      count
      ı
      fıle_count=fıle_count+1;

str=strcat('C:\Users\KkD\Documents\MATLAB\age_classıfıcatıon\last_stand\added_svm_pca\SubFunctı
ons\Feature_database\',folder(mn).name,'\',fıles(ı).name);
      I=ımread(str);


      % detect objects ın the ımage usıng haar lıke features

      Objects=ObjectDetectıon(I,'haarcascade_frontalface_alt.mat');

      Num_rows=sıze(Objects);
```

```
ıf Num_rows>1                          % check for valıd objects
   fınal_Object=sum(Objects)/(Num_rows(1));        % get an average value
else fınal_Object=Objects;
end
%ShowDetectıonResult(I,fınal_Object);

%fıgure
ım=ımcrop(I,fınal_Object);




%  ım=ımresıze(I,[256 256]);
%ımshow(ım);

%% NOSE DETECTION:
%To detect Nose
NoseDetect = vısıon.CascadeObjectDetector('Nose','MergeThreshold',10);
BB1=step(NoseDetect,ım);        % get boundıng box

Num_rows=sıze(BB1);
ıf Num_rows>1                % check for valıd data
    BB1=sum(BB1)/(Num_rows(1));
else BB1=BB1;
end

%% Eye Paır DETECTION:
%To detect Eye Paır
EyePaırDetect = vısıon.CascadeObjectDetector('EyePaırBıg','MergeThreshold',16);
BB2=step(EyePaırDetect,ım);       % get boundıng box
r=sıze(BB2);



ıf(r(1,1)==0)
```

```
   EyePaırDetect = vısıon.CascadeObjectDetector('EyePaırSmall','MergeThreshold',2);
end
BB2=step(EyePaırDetect,ım);
Num_rows=sıze(BB2);

ıf Num_rows>1                % check for valıd data
   BB2=sum(BB2)/(Num_rows(1));
else BB2=BB2;
end



% fıgure,
% ımshow(ım); hold on
% for ı = 1:sıze(BB2,1)
%     rectangle('Posıtıon',BB2(ı,:),'LıneWıdth',4,'LıneStyle','-','EdgeColor','b');
% end
% tıtle('Eye paır Detectıon');
% hold on;

%% Mouth DETECTION:
%To detect Mouth
MouthDetect = vısıon.CascadeObjectDetector('Mouth','MergeThreshold',20);
BB3=step(MouthDetect,ım);
Num_rows=sıze(BB3);

ıf Num_rows>1                % check for valıd data
   BB1=sum(BB3)/(Num_rows(1));
else BB3=BB3;
end

% fıgure,
% ımshow(ım); hold on
% for ı = 1:sıze(BB3,1)
%     rectangle('Posıtıon',BB3(ı,:),'LıneWıdth',4,'LıneStyle','-','EdgeColor','b');
```

```
% end
% tıtle('Mouth Detectıon');
% hold on;

%% Face Profıle DETECTION:
%To detect Mouth usıng weak classıfıers
FaceProfıleDetect = vısıon.CascadeObjectDetector('ProfıleFace','MergeThreshold',1);
BB4=step(FaceProfıleDetect,ım);



% fıgure,
% ımshow(ım); hold on
% for ı = 1:sıze(BB4,1)
%     rectangle('Posıtıon',BB4(ı,:),'LıneWıdth',4,'LıneStyle','-','EdgeColor','b');
% end
% tıtle('FaceProfıle Detectıon');
% hold on;



% BB1 = nose, BB2 = eyepaır, BB3 = mouth



flag=0;
BB_sıze=[sıze(BB1);sıze(BB2);sıze(BB3)];    % collect the boundıng boxes ın sıngle matrıx



for k=1:3
   ıf(BB_sıze(k,1)==0)      % str has fılemane along wıth path
      flag=1;              % ıf none of the objects ı.e. nose
      delete(str);         % eyepaır, mouth ıs detected then
   end                     % delete the ımage fıle from traınıng folder
end
```

```
if flag==0

    %% Preprocessing of image


    [r, c, p]=size(im);      % checking weather image is coloured or not
    if p==3                  % if coloured then convert into gray
       im2 = rgb2gray(im);  % convert to grayscale
    else
       delete(str);         % delete the image file from training folder
    end


    %
    % imshow(im2)
    % figure
    im2 = imadjust(im2,stretchlim(im2),[]);     % Adjust the contrast of the image, specifying contrast limits.
    % imshow(im2)
    % figure
    im2=histeq(im2);                    % Enhance contrast using histogram equalization
    % imshow(im2)

    %im2=medfilt2(im2,[3 3]);
    im2 = filter2(fspecial('average',3),im2)/255;  % 2-D digital filter using predefined 2-D averaging filter
    % figure, imshow(im2)
    [Gmag, Gdir]=imgradient(im2,'sobel');            % Gradient magnitude and direction of an image using Sobel gradient operator
    %im3= edge(im2,'Sobel',0.02);
    % figure, imshow(Gmag)
    im3=im2bw(Gmag,graythresh(Gmag));             % convert to black and white
    % figure,imshow(im3);
```

```
% crop the gradıent ımage
% crop to get forehead regıon
%       BB = [ x, y, w, h]
% BB1 = nose, BB2 = eyepaır, BB3 = mouth

ımfull = ım;


ım2A=ımcrop(Gmag,[BB2(1,1) fınal_Object(1,2) BB2(1,3) -fınal_Object(1,2)+BB2(1,2)]);  % forehead
%       fıgure(1),ımshow(ım2A)
%       hold on

% crop to get left eyelıd regıon
ım2B=ımcrop(Gmag,[BB2(1,1) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]);  % left eyebrow
%       fıgure(2),ımshow(ım2B)
%       hold on

% crop to get rıght eyelıd regıon
ım2C=ımcrop(Gmag,[BB1(1,1)+BB1(1,3) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]); % rıght eyebrow
%       fıgure(3),ımshow(ım2C)
%       hold on

% crop to get left eye corner regıon
ım2D=ımcrop(Gmag,[fınal_Object(1,1)-(-BB2(1,1)+fınal_Object(1,1))*2/3 BB2(1,2) (BB2(1,1)-fınal_Object(1,1))*2/3 BB2(1,4)]);  % left cheek
%       fıgure(4),ımshow(ım2D)
%       hold on

% crop to get rıght eye corner regıon
ım2E=ımcrop(Gmag,[BB2(1,1)+BB2(1,3) BB2(1,2) (BB2(1,1)-fınal_Object(1,1))*2/3 BB2(1,4)]);  % rıght cheek
```

```
%           figure(5),imshow(im2E)
%           hold on

% convert to double precision
im2A=double(im2A);
im2B=double(im2B);
im2C=double(im2C);
im2D=double(im2D);
im2E=double(im2E);
im4=~im3;

% figure,imshow(im4);

% crop the black and white image

% do the same as above but on lack and white processed image

im3=double(im3);

im3A=imcrop(im3,[BB2(1,1) final_Object(1,2) BB2(1,3) -final_Object(1,2)+BB2(1,2)]);
im3B=imcrop(im3,[BB2(1,1) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]);
im3C=imcrop(im3,[BB1(1,1)+BB1(1,3) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]);
im3D=imcrop(im3,[final_Object(1,1)-(-BB2(1,1)+final_Object(1,1))*2/3  BB2(1,2)  (BB2(1,1)-
final_Object(1,1))*2/3 BB2(1,4)]);
im3E=imcrop(im3,[BB2(1,1)+BB2(1,3) BB2(1,2) (BB2(1,1)-final_Object(1,1))*2/3 BB2(1,4)]);

%im3_fh=imcrop(im3,[final_Object(1,1:2) final_Object(1,1)-BB2(1,1) BB2(1,2)])
% figure
% imshow(im3A)
% figure
% imshow(im3B)
% figure
% imshow(im3C)
% figure
```

```
% ımshow(ım3D)
% fıgure
% ımshow(ım3E)



% convert to double precısıon
ım3A=double(ım3A);
ım3B=double(ım3B);
ım3C=double(ım3C);
ım3D=double(ım3D);
ım3E=double(ım3E);


W1=(sum(sum(ım3A)));       % ıs the number of wrınkle pıxels ın forehead regıon
M1=(sum(sum(ım2A)));       % the canny edge magnıtude of wrınkle pıxel
P1=length(ım3A)^2;         % square of the number of pıxels

W2=(sum(sum(ım3B)));       % sum of pıxels ın left eyelıd regıon
M2=(sum(sum(ım2B)));
P2=length(ım3B)^2;

W3=(sum(sum(ım3C)));       % sum of pıxels ın rıght eyelıd regıon
M3=(sum(sum(ım2C)));
P3=length(ım3C)^2;

W4=(sum(sum(ım3D)));       % sum of pıxels ın left eye corner regıon
M4=(sum(sum(ım2D)));
P4=length(ım3D)^2;

W5=(sum(sum(ım3E)));       % sum of pıxels ın rıght eye corner regıon
M5=(sum(sum(ım2E)));
P5=length(ım3E)^2;
```

```
W=W1+W2+W3+W4+W5;          % sum of the pıxels of the black and whıte ımage
P=P1+P2+P3+P4+P5;          % sum of the square of length of all the detected regıons
M=M1+M2+M3+M4+M5;          % sum of the pıxels of the gradıent ımage

% BB = [ x, y, w, h]
% BB1 = nose, BB2 = eyepaır, BB3 = mouth

% get the straıght lıne vector between center of mouth and left
% eye

v1 = [-BB3(1,1)-BB3(1,3)/2+BB2(1,1), -BB3(1,2)-BB3(1,4)+BB2(1,2)];

% get the straıght lıne vector between center of mouth and
% rıght eye

v3 = [BB3(1,1)+BB3(1,3)/2-BB2(1,1)+BB2(1,3), BB3(1,2)+BB3(1,4)-BB2(1,2)+BB2(1,4)];

u1 = v1 / norm(v1);
u3 = v3 / norm(v3);



% Paırwıse dıstance between paırs of objects
% BB1 = nose, BB2 = eyepaır, BB3 = mouth

R1=BB2(3);                          %  dıstance between both eyes
R2=pdıst([BB2(1:2);BB3(1:2)],'euclıdean');      %  dıstance between eye paır and mouth
R3=pdıst([BB2(1:2);BB1(1:2)],'euclıdean');      %  dıstance between eye paır and nose
R4=pdıst([BB2(1:2);fınal_Object(1,1)+fınal_Object(1,4)
fınal_Object(1,1)+(fınal_Object(1,3))/2],'euclıdean'); %  dıstance b/w eye paır and chın

F1=R1/R3;  % F1 = (dıstance from left to rıght eye ball) / (dıstance from eye to nose)
F2=R1/R2;  % F2 = (dıstance from left to rıght eye ball) / (dıstance from eye to lıp)
F3=R3/R4;  % F3 = (dıstance from eye to nose) / (dıstance from eye to chın)
F4=R3/R2;  % F4 = (dıstance from eye to nose) / (dıstance from eye to lıp)
```

```
        %%

           WFULL = (sum(sum(ımfull)));
           MFULL = (sum(sum(ımfull)));
           PFULL = length(ımfull)^2;


        %%

        F5= (W)/(P);                % Wrınkle Densıty
        F6=(M)/(255*abs(W));          %
        F7=M/(255*P);                % Average Skın Varıance
        F8 = acos(dot(u1, u3)) ;       % get the angle by dot product of the two mormalızed vectors

        fınal_feature=[F1,F2,F3,F4,F5,F6,F7,F8];
        fea=[fea;fınal_feature];
        group=[group, count];

      else
        group=[group];
      end
   end
end

% save haar_features fea group
```

Neural_net.m

```
clc;clear;close all;warnıng off all;

load haar_features;
```

```
class = zeros(3,numel(group));      % create 3x212 matrıx

for ı =1:numel(unıque(group))
   class(ı,:) = group == ı;
end

class_t = class';



[a, b]= uıgetfıle('*.*');

fılename = fullfıle(b,a);

[test_sample] = open_test_sample(fılename);

x = fea';
t = class_t';

% Choose a Traınıng Functıon
% For a lıst of all traınıng functıons type: help nntraın
% 'traınlm' ıs usually fastest.
% 'traınbr' takes longer but may be better for challengıng problems.
% 'traınscg' uses less memory. Suıtable ın low memory sıtuatıons.
traınFcn = 'traınscg';  % Scaled conjugate gradıent backpropagatıon.

% Create a Pattern Recognıtıon Network
hıddenLayerSıze = 10;
net = patternnet(hıddenLayerSıze);

% Setup Dıvısıon of Data for Traınıng, Valıdatıon, Testıng
net.dıvıdeParam.traınRatıo = 70/100;
net.dıvıdeParam.valRatıo = 15/100;
net.dıvıdeParam.testRatıo = 15/100;
```

```
% Traın the Network
[net,tr] = traın(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y);
tınd = vec2ınd(t);
yınd = vec2ınd(y);
percentErrors = sum(tınd ~= yınd)/numel(tınd);

% Vıew the Network
% vıew(net);


% test the sample
test_n = net(test_sample');
test_ındex = vec2ınd(test_n)


ıf test_ındex==1
   msgbox('Adult');

elseıf test_ındex==2
   msgbox('Chıld');

elseıf test_ındex==3
   msgbox('Old');

end


% Plots
```

```
% Uncomment these lınes to enable varıous plots.
% fıgure, plotperform(tr)
% fıgure, plottraınstate(tr)
% fıgure, ploterrhıst(e)
% fıgure, plotconfusıon(t,y)
% fıgure, plotroc(t,y)
```

knn_classıfıcatıon.m

```
clc;
clear;
close all;
warnıng off all;
%% Varıable declaratıons

[a, b]= uıgetfıle('*.*');
b=[b a];
I=ımread(b);
clear a;
clear b;

%%

% FDetect = vısıon.CascadeObjectDetector;
%
% %Returns Boundıng Box values based on number of objects
% BB = step(FDetect,I);
% fıgure,
% ımshow(I); hold on
% for ı = 1:sıze(BB,1)
%     rectangle('Posıtıon',BB(ı,:),'LıneWıdth',5,'LıneStyle','-','EdgeColor','r');
% end
% tıtle('Face Detectıon');
% hold on;
```

```
f=dır('C:\Users\KkD\Documents\MATLAB\age_classıfıcatıon\last_stand\added_svm_pca\SubFunctıons\
*.xml');

for ı=1:length(f)
   fılename=f(ı).name;
   ConvHaar_casade_OpenCV(fılename(1:end-4));
end

HaarCascade=Get_Haar_Casade('haarcascade_frontalface_alt.m');
Objects=ObjectDetectıon(I,'haarcascade_frontalface_alt.mat');
Num_rows=sıze(Objects);

ıf Num_rows>1
   fınal_Object=sum(Objects)/(Num_rows(1));
else fınal_Object=Objects;
end

ShowDetectıonResult(I,fınal_Object);

fıgure
ım=ımcrop(I,fınal_Object);
%  ım=ımresıze(I,[256 256]);
ımshow(ım);

%% NOSE DETECTION:
%To detect Nose
NoseDetect = vısıon.CascadeObjectDetector('Nose','MergeThreshold',10);
BB1=step(NoseDetect,ım);
% fıgure,
% ımshow(ım); hold on
for ı = 1:sıze(BB1,1)
   rectangle('Posıtıon',BB1(ı,:),'LıneWıdth',4,'LıneStyle','-','EdgeColor','b');
```

```
end
tıtle('Nose Detectıon');
hold on;

%% Eye Paır DETECTION:
%To detect Eye Paır
EyePaırDetect = vısıon.CascadeObjectDetector('EyePaırBıg','MergeThreshold',16);

BB2=step(EyePaırDetect,ım);
r=sıze(BB2);

ıf(r(1,1)==0)
   EyePaırDetect = vısıon.CascadeObjectDetector('EyePaırSmall','MergeThreshold',1);
end
BB2=step(EyePaırDetect,ım);

% fıgure,
% ımshow(ım); hold on

for ı = 1:sıze(BB2,1)
   rectangle('Posıtıon',BB2(ı,:),'LıneWıdth',4,'LıneStyle','-','EdgeColor','b');
end
tıtle('Eye paır Detectıon');
hold on;


%% Mouth DETECTION
%To detect Mouth
MouthDetect = vısıon.CascadeObjectDetector('Mouth','MergeThreshold',20);
BB3=step(MouthDetect,ım);
% fıgure,
% ımshow(ım); hold on
for ı = 1:sıze(BB3,1)
   rectangle('Posıtıon',BB3(ı,:),'LıneWıdth',4,'LıneStyle','-','EdgeColor','b');
```

```
end
tıtle('Mouth Detectıon');
hold on;



%% Face profıle DETECTION:
%To detect Mouth
FaceProfıleDetect = vısıon.CascadeObjectDetector('ProfıleFace','MergeThreshold',1);
BB4=step(FaceProfıleDetect,ım);
% fıgure,
% ımshow(ım); hold on
for ı = 1:sıze(BB4,1)
   rectangle('Posıtıon',BB4(ı,:),'LıneWıdth',4,'LıneStyle','-','EdgeColor','b');
end
tıtle('FaceProfıle Detectıon');
hold on;



%% Preprocessıng of ımage

ım2=rgb2gray(ım);
ımshow(ım2);
fıgure;

ım2 = ımadjust(ım2,stretchlım(ım2),[]);
ımshow(ım2);
fıgure;

ım2=hısteq(ım2);
ımshow(ım2);

%ım2=medfılt2(ım2,[3 3]);
ım2 = fılter2(fspecıal('average',3),ım2)/255;
```

```
% fıgure, ımshow(ım2);

[Gmag, Gdır]=ımgradıent(ım2,'sobel');
fıgure, ımshow(Gmag)

ım3=ım2bw(Gmag,graythresh(Gmag));
fıgure,ımshow(ım3);


% se = strel('square',2);        %structural element used ın morphologıcal operatıon
% ım3 = ımdılate(ım3,se);          % ımdılate wıll shrınk the ımage
% ımshow(ım3);
% hold on;
% ı4 = ımfıll(ım3,'holes');

ım2A=ımcrop(Gmag,[BB2(1,1) fınal_Object(1,2) BB2(1,3) -fınal_Object(1,2)+BB2(1,2)]);
ım2B=ımcrop(Gmag,[BB2(1,1) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]);
ım2C=ımcrop(Gmag,[BB1(1,1)+BB1(1,3) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]);
ım2D=ımcrop(Gmag,[fınal_Object(1,1)-(-BB2(1,1)+fınal_Object(1,1))*2/3        BB2(1,2)        (BB2(1,1)-
fınal_Object(1,1))*2/3 BB2(1,4)]);
ım2E=ımcrop(Gmag,[BB2(1,1)+BB2(1,3) BB2(1,2) (BB2(1,1)-fınal_Object(1,1))*2/3 BB2(1,4)]);


ım2A=double(ım2A);
ım2B=double(ım2B);
ım2C=double(ım2C);
ım2D=double(ım2D);
ım2E=double(ım2E);
ım4=~ım3;


fıgure,ımshow(ım4);

ım3=double(ım3);
```

```
ım3A=ımcrop(ım3,[BB2(1,1) fınal_Object(1,2) BB2(1,3) -fınal_Object(1,2)+BB2(1,2)]);
ım3B=ımcrop(ım3,[BB2(1,1) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]);
ım3C=ımcrop(ım3,[BB1(1,1)+BB1(1,3) BB1(1,2) -BB2(1,1)+BB1(1,1) BB1(1,4)]);
ım3D=ımcrop(ım3,[fınal_Object(1,1)-(-BB2(1,1)+fınal_Object(1,1))*2/3 BB2(1,2) (BB2(1,1)-
fınal_Object(1,1))*2/3 BB2(1,4)]);
ım3E=ımcrop(ım3,[BB2(1,1)+BB2(1,3) BB2(1,2) (BB2(1,1)-fınal_Object(1,1))*2/3 BB2(1,4)]);

%ım3_fh=ımcrop(ım3,[fınal_Object(1,1:2) fınal_Object(1,1)-BB2(1,1) BB2(1,2)])

fıgure
ımshow(ım3A)
fıgure
ımshow(ım3B)
fıgure
ımshow(ım3C)
fıgure
ımshow(ım3D)
fıgure
ımshow(ım3E)


ım3A=double(ım3A);
ım3B=double(ım3B);
ım3C=double(ım3C);
ım3D=double(ım3D);
ım3E=double(ım3E);

v1 =[-BB3(1,1)-BB3(1,3)/2+BB2(1,1), -BB3(1,2)-BB3(1,4)+BB2(1,2)];
v3 = [BB3(1,1)+BB3(1,3)/2-BB2(1,1)+BB2(1,3), BB3(1,2)+BB3(1,4)-BB2(1,2)+BB2(1,4)];

u1 = v1 / norm(v1);
u3 = v3 / norm(v3);
```

```
W1=(sum(sum(ım3A)));
M1=(sum(sum(ım2A)));
P1=length(ım3A)^2;

W2=(sum(sum(ım3B)));
M2=(sum(sum(ım2B)));
P2=length(ım3B)^2;

W3=(sum(sum(ım3C)));
M3=(sum(sum(ım2C)));
P3=length(ım3C)^2;

W4=(sum(sum(ım3D)));
M4=(sum(sum(ım2D)));
P4=length(ım3D)^2;

W5=(sum(sum(ım3E)));
M5=(sum(sum(ım2E)));
P5=length(ım3E)^2;

W=W1+W2+W3+W4+W5;
P=P1+P2+P3+P4+P5;
M=M1+M2+M3+M4+M5;

R1=BB2(3);
R2=pdıst([BB2(1:2);BB3(1:2)],'euclıdean');
R3=pdıst([BB2(1:2);BB1(1:2)],'euclıdean');
R4=pdıst([BB2(1:2);fınal_Object(1,1)+fınal_Object(1,4)
fınal_Object(1,1)+(fınal_Object(1,3))/2],'euclıdean');

F1=R1/R3;
F2=R1/R2;
F3=R3/R4;
F4=R3/R2;
```

```
F5= (W)/(P);
F6=(M)/(255*abs(W));
F7=M/(255*P);
F8 = acos(dot(u1, u3)) ;


%
% for ı=1:length(Objects)
%     rectangle('Posıtıon',Objects(ı,1:4),'LıneWıdth',4,'Lınestyle','-','EdgeColor','g');
% end

%% KNN Classıfıcatıons

load haar_features

traın_set_1=fea(:,1:4);

test_set_1=[F1 F2 F3 F4];

class=group';

result=knnclassıfy(test_set_1,traın_set_1,class,1,'cosıne','nearest');


ıf result == 2
   msgbox('Chıld')
else

   traın_set_2=fea(:,5:8);
   test_set_2=[F5 F6 F7 F8];
   class=group';

      result = knnclassıfy(test_set_2,traın_set_2,class,1,'cosıne','nearest');
```

```
    ıf result ==1
        msgbox('Adult')
    elseıf result == 3
        msgbox('senıor')
    end
end
```