International Journal of Progressive Sciences and Technologies (IJPSAT)
ISSN: 2509-0119.

Vol. 34 No. 1 August 2022, pp. 49-72

Development Of Iris Based Age And Gender Detection System

Faluyi Bamidele Ibitayo[1], Ojo Olufemi Ariyo[2], Atobatele Oluwatobi O.[3]

[1]Department of Computer Science
The Federal Polytechnic, Ado-Ekiti. Ekiti State.
Nigeria
Faluyi_bi@fedpolyado.edu.ng

[2]Department of Computer Science
The Federal Polytechnic, Ado-Ekiti. Ekiti State.
Nigeria
Ojo_oa@fedpolyado.edu.ng

[3]Department of Computer Science
The Federal Polytechnic, Ado-Ekiti. Ekiti State.
Nigeria
Oluwatunmise_ao@fedpolyado.edu.ng

Abstract— Biometric recognition has shown their utility in different aspect including reducing search space significantly which has led to improve recognition performance, reduced computation time and faster processing time, a person is identified automatically by processing the unique features that are posed by the individual. The existing biometric systems recognize and accept a person, else simply reject a person if not enrolled, but these systems do not give software attributes of a person which is needed to search impostor as it has been observed in many occasions and especially in Nigeria that identification of an individual's age and gender does not go beyond physical factors which in most cases can be manipulated or spoofed to carry out nefarious activities. This project focuses on developing an iris-based age and gender detection system for certain individuals to identify a person in real time. Left and right irises of 190 subjects constituting 1,716 images were acquired and Five Hundred and Seventy (570) left Irises were normalized to a uniform size of 250 by 250 pixels. Three Hundred and Forty-Two (342) images were used for training while the remaining Two Hundred and Twenty-Eight (228) were used for testing. The acquired images were preprocessed by performing segmentation, filtering and normalization using Daugman's Rubber Sheet Model. Deep learning pre-trained networks are adopted to extract features from iris images. Further, these features are trained and classified using the multi-class Support Vector Machines (SVM) model for performance evaluation of the system. The system was implemented in Matrix Laboratory 9.0 (R2016a). The performance of the system was evaluated using accuracy, precision, recall and False Positive Rate (FPR). The hypothesis stating 'the iris has age, and gender-related information' is proven correct from experimental results. The evaluation results showed that False Positive Rate, Recall, Precision and Accuracy of gender prediction were 2.19%, 92.31%, 96.55% and 95.62% respectively at 0.75 threshold while for age prediction, the best values were obtained at age group of 20-24 for FPR, Recall, Precision and Accuracy which were 5.61%, 94.37%, 96.18% and 94.38% respectively. The developed model gave good performance with high recognition accuracy, recall, precision and low FPR values. Therefore, the developed model can be used in all firms and industries where security and personal identification is desired for security purpose and in going through investigation of criminal records for detecting age and gender of individuals.

Keywords—biometrics, iris, predictioin, fingerprint, recognition, feature extraction.

I. Introduction

Nowadays, biometric recognition is becoming one of the most promising and reliable way to authenticate the identity of a person. Biometric feature can serve as a kind of living passport or a living password that one need not remember but one always carried along. And iris-based identification has been receiving more and more attention since its emergence in 1992.

Human iris is believed to present a lavish set of individual features, distinguishing even identical twins, Iris recognition is the process of recognizing a person by analysing the random pattern of the iris as shown in figure 1.1. The iris is a muscle within the eye that regulates the size of the pupil, controlling the amount of light that enters the eye. It is the coloured portion of the eye with colouring based on the amount of melatonin pigment within the muscle (Daugman, 1999). A good biometric feature should be:

a. High uniquely: so, the chance of two people with the same feature will be very small

b. Easily captured: should be convenient and should avoid intrusion to the users.

c. Permanence: Characteristic should not change with time

d. Collectability: Characteristic should be measured quantitatively

Iris as a biometric feature can fulfill all the requirements mentioned above.

Earlier, the personal identification of individuals was done through a secret password, encoded cards and personal identification number. The quest for a non-invasive method of identification leads to the ground breaking concept of iris recognition. It was first patented by US ophthalmologist (Flom and Safir, 1987). Later, an automated system for iris recognition was developed at Los Alamos National Laboratories (Johnson, 1991). Followed by it, Daugman and Wildes have worked independently and developed prototypes. Wildes (1997) has also discussed briefly on the emergence of this iris-based biometric technology. Based on the table of information furnished in (Nandakumar *et. al.,* 2008), Iris seems to be a better biometric trait in terms of having less false rejection rate and false accept rate.

Soft biometric attributes such as gender, age, ethnicity, weight, height, body mass index and so on need to be identified from biometrics data stored in a system. In iridology, the characteristics of the iris can be examined to determine the health status of the body parts. The diseases like blood pressure, diabetes and kidney problems, lung diseases, etc. can be diagnosed from human iris. Researchers also attempted to identify age and gender from the human iris. Estimating gender and age from human iris is a challenging task, but have applications in many fields like controlling the information content on media or internet based on age limit. Other applications include forensic sciences, law enforcement, security controls, demographic information collection, and real time electronic marketing, etc. It also helps to speed up the matching process if these attributes of a person are known.

In the area of classification, Image classification is an important and challenging task in various application domains, including biomedical imaging, biometry, video surveillance, vehicle navigation, industrial visual inspection, and remote sensing. Age and gender classification from iris texture are also an active and expanding research area that has made use of these several image classification techniques. In natural science, few attempts have been made to perform automatic age and gender classification based on human images. But in Computer Science, age and gender classification makes use of different algorithms and it includes three basic modules: image pre-processing, feature extraction, and training.

Specifically, in this paper we propose an approach to the age and gender prediction task which, while demonstrating the viability of iris-based age and gender prediction per se, also uses only simple geometric features extracted from iris images, and is thus fast and efficient in implementation in comparison with the previous study reported in (Sgroi *et. al.,* 2013).

II. Literature Review

A. Biometric Technology

A biometric system provides automatic recognition of an individual based on some sort of unique feature or characteristic possessed by the individual. Biometric systems have been developed based on fingerprints, facial features, voice, hand geometry, handwriting, the retina (Sanderson and Erbetta, 2000), and iris. Biometric systems work by first capturing a sample of the feature, such as recording a digital sound signal for voice recognition, or taking a digital colour image for face recognition. The sample is then transformed using some sort of mathematical function into a biometric template. The biometric template will provide a normalised, efficient and highly discriminating representation of the feature, which can then be objectively compared with other templates in order to determine identity. Most biometric systems allow two modes of operation. An enrolment mode for adding templates to a database, and an identification mode, where a template is created for an individual and then a match is searched for in the database of pre-enrolled templates.

This chapter dealt with distinctive research works, which has been completed in iris recognition field. Related works to subject under disclosure were reviewed in this chapter with a focus on the approach adopted, their strength and as well as noticeable drawbacks from such work.

Multi-Biometrics Involving the Iris

The term “multi-biometric” is used to refer to techniques that use more than one biometric sample in making a decision. Often the samples are from different sites on the body; for example, iris and fingerprint. Also, they might be from different sensing modalities; for example, 3D and 2D. Or they might be repeated samples from the same sensor and site on the body. The motivation for multi-biometrics is to:

i. increase the fraction of the population for which some usable sample can be obtained, and / or

ii. increase recognition accuracy, and / or

iii. make it more difficult to spoof a biometric system.

In India’s Unique ID program (Ricanek, 2011) in many ways the most ambitious biometrics application in the world to date, iris and fingerprint are used primarily, it seems, to increase coverage of the population.

Most multi-biometric work involving the iris has looked at combining iris with some other biometric site, rather than multiple sensing modalities for iris, or repeated iris samples. Papers have been published looking at almost any combination of iris and some other modality that one can imagine. Often the practical motivation for the particular pairing is not clear. The vast majority of this work has used chimera subjects; that is, virtual subjects created by pairing together biometric samples from already existing uni-modal datasets. For example, several papers use iris images from a CASIA dataset and face images from the ORL biometric datasets, to use datasets representing a much larger number of subjects and images than in the ORL face dataset or the CASIA v1 iris dataset, and to compare performance of the multi-biometric approach to performance of state-of-the art algorithms for the individual biometrics. In the summaries below, we have tried to explicitly note the few instances where the dataset used was not chimeric.

Perhaps naturally, the largest cluster of papers in this area deals with the combination of face and iris. This group of publications is multi-biometric both in the sense of combining iris and face, and often also in the sense of using near infrared illumination (for iris) and visible light (for face). Gan and Liu (2009) applied a discrete wavelet transform to face and iris images, and use a kernel Fischer Discriminate analysis, with chimera subjects created from the ORL face database and (apparently) the CASIA v1 iris database. Liu *et al.* (2009) experimented with a 40-person chimera dataset made from ORL face images and CASIA iris images, with relatively low performance.

Vatsa *et al.* (2009) considered approaches based on multiple iris samples. They use elements of belief function theory for iris-based multi-biometrics and look at two scenarios: combining results from enrolling one iris with two images and combining results from the left and right iris each enrolled with one image.

Baig *et al.* (2009) investigated iris and fingerprint fusion using the Masek algorithm and a SUNYBuffalo algorithm, respectively, experimenting on a West Virginia University dataset. It is noted that performance is relatively low, due to design for a “small memory footprint real time system”. Elmadani (2009) presented the “fingerIris” algorithm for combination of iris and fingerprint. The approach is evaluated on a true multibiometric dataset representing 200 individuals. The system gets 4 to 5 false reject and / or false accept results on this dataset, depending on the setting of the decision threshold.

Wang *et al.* (2009) explored score-level fusion of iris matching and palm print matching using an apparently chimera dataset representing 100 persons.

Hollingsworth *et al.* (2009) presented an approach that uses multiple iris samples taken using the same sensor, taking advantage of temporal continuity in an iris video to improve matching performance. They select multiple frames from an iris video, unwrap the iris into polar form, and then average multiple frames together. They find that this image-level fusion yield better matching performance than previous multi-gallery score fusion methods.

Zuo *et al.* (2010) investigated the possibility of matching between a visible-light image and a NIR image of the iris. They formulate a method to estimate the NIR iris image from a color image. It is claimed that this approach "achieves significantly high performance compared to the case when the same NIR image is matched against R (red) channel alone".

B. Iris Image Acquisition

There are still major research issues in the area of iris image acquisition. One issue involves imaging the iris with a sensor system that allows the person to be more "at a distance" and "on the move". Matey and Kennell (2009) presented a comprehensive tutorial on the issues involved in acquiring iris images at a distance of greater than one meter. The tutorial includes a partial list of commercial iris recognition devices released between 1995 and 2008 and a description of several successful applications of iris biometrics. The authors describe acquisition issues including the wavelength of light used, the type of light source, the amount of light reflected by the iris back to the sensor, required characteristics of the lens, signal to noise ratio, eye safety, and image quality. Capture volume, residence time, and sensitivity to subject motion are also discussed.

Wheeler *et al.* (2008) described a prototype "stand-off" iris recognition system designed to work at sensor-to-subject distances of up to 1.5 m. The system uses two wide-field-of-view cameras to perform face location in the scene and an iris camera and illuminator to image the iris. Dong *et al.* (2009) discussed the design of a system to image the iris "at a distance", allowing a standoff of 3 meters. Although current commercial iris biometrics systems all use near-infrared (NIR) illumination, and most research assumes NIR imaging similar to that used in current commercial sensors, (Proenca, 2009) argued for visible wavelength imaging as the more appropriate means to achieve "at a distance" and "on the move" imaging. Boddeti and Kumar (2010) investigated the use of wavefront-coded imagery for iris recognition. This topic has been discussed in the literature before, but Boddeti and Kumar use a larger data set and present experiments to evaluate how different parts of the recognition pipeline (e.g. segmentation, feature extraction) are affected by wavefront coding. They propose using unrestored image outputs from the wavefront-coded camera directly, and test this idea using two different recognition algorithms. They conclude that wavefront coding could help increase the depth of field of an iris recognition system by a factor of four, and that the recognition performance on unrestored images was only slightly worse than the performance on restored images.

There is little published work dealing with imaging the iris under different wavelength illumination. Ross *et al.* (2009) looked at imaging the iris with illumination in the 950nm to 1650nm range, as opposed to the 700nm to 900nm range typically used in commercial systems. They suggest that it is possible to image different iris structure with different wavelength illumination, raising the possibility of multi-spectral matching as a means to increased recognition accuracy. Grabowski *et al.* (2009) described an approach to iris imaging that is meant to allow characterization of structures in the iris tissue over changes in pupil dilation.

McCloskey *et al.* (2010) explored a technique termed "flutter shutter" as a means to acquire sharply-focused iris images from moving subjects. The idea is that the camera shutter "lutters" between open and closed while the sensor accumulates an image, from which an appropriately-designed deblurring algorithm can then recover an in-focus image.

a) Non-Ideal Images and Quality Metrics

As mentioned earlier, one important current research emphasis is acquisition of images under less constrained conditions. As iris images are acquired under less constrained conditions, the issue of image quality becomes more important and complex. Another element of this is the design of algorithms meant to handle "non ideal" or "noisy" images. While it is not part of the image acquisition step per se, iris biometric systems typically evaluate the focus quality, and possibly other factors, of each candidate image in order to select usable images. Ren and Xie (2009) proposed approaches to evaluating image focus quality that involve finding the iris region before computing the focus value. While iris biometric systems select images based in part on focus quality, there are few publications dealing with deblurring of iris images.

He *et al.* (2008) estimated the user distance from the sensor in order to estimate the appropriate point spread function (PSF) for image restoration. They measure the distance between two specular highlights on the iris. Using this information, plus knowledge about the positions of the two infrared LEDs, they get the user's distance from the camera without using a special distance sensor. The knowledge of the distance from the sensor is used in estimating the PSF.

Kalka *et al.* (2010) investigated a number of image quality factors, including percent occlusion, defocus, motion blur, gaze deviation, amount of specular reflection on the iris, lighting variation on the iris, and total pixel count on the iris. In evaluating various data sets, they found that the ICE data had more defocused images, the WVU data had more lighting variation, and the CASIA data had more occlusion than the other sets.

Proenca (2010) presented an approach to quality assessment of iris images acquired in the visible-light domain. Factors considered in the quality assessment include focus, motion, angle, occlusions, area, pupillary dilation and levels of iris pigmentation. The claim is that by using the output of the segmentation phase in each assessment, the method is able to handle severely degraded samples.

b) Image Compression

Daugman and Downing (2008) presented a detailed study of the effects of compression of the original iris image on the performance of iris biometrics. They present schemes that combine isolation of the iris region with JPEG and JPEG 2000 compression, evaluate their approach on images from the Iris Challenge Evaluation (ICE) 2005 dataset and conclude that it is "possible to compress iris images to as little as 2000 bytes with minimal impact on recognition performance."

Konrad *et al.* (2009) aimed to compress iris data without degrading matching results. They use JPEG compression on unwrapped polar iris images. They design and compare different quantization tables to use with the JPEG compression. Two of their tested Q-tables are designed to preserve more angular iris texture than radial iris texture (i.e. the horizontal texture in the unwrapped image). The other two Q- tables are derived from the first two through genetic optimization. There is no clear winner among their tested Q-tables, and they conclude that custom Q-tables for iris recognition should be optimized to a specific target bitrate for best performance.

Hammerle-Uhl *et al.* (2009) used JPEG 2000 compression on original iris images. They aim to improve compression performance by using region-of-interest coding. They detect the iris using edge detection and a Hough transform, then set the ROI to the detected candidate circle with largest radius inside a certain allowed range. They compare compression with and without ROI coding and find that match scores improve and error rates decrease when using the ROI coding.

C. Iris Region Segmentation

Publications related to segmenting the iris region constitute a significant fraction of the published work in iris biometrics. Many of these publications can be grouped as tackling similar versions of the traditional iris segmentation problem; e.g., given one still image, find the pupillary and limbic boundaries. However, there are also a variety of approaches being explored to find occlusion by specular highlights and eyelashes, to segment the iris using less-constrained boundaries, and to refine initial segmentation boundaries.

Iris segmentation algorithms that assume circular boundaries for the iris region continue to appear in some conferences. Publications also continue to appear that propose iris segmentation techniques that are evaluated on the CASIA version 1 dataset. Again, we have chosen not to cover this subarea of work in this survey. The use of the CASIA v1 dataset to evaluate iris segmentation algorithms is inherently problematic, because the images have been edited to have a circular region of constant intensity value for the region of each Iris (Phillips *et al.,* 2009). Therefore, any segmentation algorithm built around the assumption of a circular region of constant dark intensity value should naturally meet with great success on this dataset, even though these conditions are generally not present in the iris region of real images.

A number of researchers have considered various approaches to segmenting the iris with boundaries not constrained to be circles. Wibowo and Maulana (2009) evaluated an approach using the CASIA v1 data and their own dataset of 30 visible-light iris images. Labati *et al.* (2009) proposed methods to find the pupil center and then to find the inner and outer iris boundaries, presenting experimental results on CASIA v3 and UBIRIS v2 images.

Chen *et al.* (2009) considered an approach to segmenting the iris region under less constrained conditions, experimenting with the UBIRIS v2 visible-light iris image dataset, and placing in the top six in the NICE competition. Broussard and Ives train a neural net to classify pixels in an iris image as either being on an iris boundary or not, selecting the most useful eight features from a pool of 322 possible features. Subjective visual evaluation of results indicates improvement over methods that assume circular boundaries. Zuo and Schmid (2010) presented an approach to segmenting the iris using ellipses for the pupillary and the limbic boundaries, with experiments on CASIA, ICE and WVU datasets. Pan et al. detect edge points using their method on CASIA v2 and CASIA v3 twin's data sets.

Roy and Bhattacharya (2009) suggested a segmentation method using geometric active contours. They apply opening operators to suppress interference from eyelashes. Next, they approximate elliptical boundaries for the pupil and limbic boundaries. They refine the detected boundary using geometric active contours (i.e., active contours implemented via level set) to a narrow band over the estimated boundary. They fit parabolic curves to the upper and lower eyelids. To isolate the eyelashes, they use 1D Gabor filters and variance of intensity. Roy and Bhattacharya also describe a level set style active contour method for finding the pupil and iris boundaries in non-ideal iris images, presenting results on the UBIRIS v2, ICE 2005 and WVU non-ideal iris datasets.

He *et al.* (2008) acknowledged the difficulty of detecting and removing specular highlights in the iris image and present an interesting multi-sample approach to this problem. They assume that multiple images of the same iris are available, with the specular highlights appearing in different places on the iris in different images.

Kalka *et al.* (2009) tackled the problem of predicting or detecting when iris segmentation has failed, with experiments on the WVU and ICE datasets, and on two iris segmentation algorithms. Proenca (2010) observed that images acquired in the visible wavelength in less-constrained environments tend to have noise that results in severely degraded images. Whereas many iris biometric segmentation algorithms key on the pupil to anchor the segmentation, he proposes to anchor the segmentation on the sclera as much more naturally distinguishable than any other part of the eye. The sclera also provides a useful constraint, in that it must be immediately adjacent on both sides of the iris. One of the differences in iris biometrics processing for visible-light versus near-IR images, is that the pupillary boundary tends to be more distinct in near-IR whereas the limbic boundary appears to be more distinct in visible light.

Lee *et al.* (2009) described a way to locate and analyze eyes in the MBGC portal videos. They use the Viola-Jones detector that comes with OpenCV and is trained to detect eye pairs. They measure the edge density in an image to determine the focus level and select appropriate frames from the video. The Iris BEE algorithm is used for segmentation and feature extraction. Eyes from the MBGC porta videos are compared to higher-quality still iris images. The two-eye detection rate in the videos was 97.7%. The segmentation rate was 81.5%, and the matching rate was 56.1%. This matching rate is low compared to typical iris recognition systems, likely reflecting the low level of iris image quality in the MBGC portal videos.

Thompson and Flynn (2010) presented a method of improving the recognition performance of iris biometrics by perturbing parameters of the iris segmentation. The perturbations generate a set of alternate segmentations, and so also alternate iris codes, which effectively result in an improved authentic distribution.

D. Feature Coding and Matching

Performing texture analysis to produce a representation of the iris texture, and the matching of such representations, is at the core of any iris biometric system. A large fraction of the publications in iris biometrics deal with this area. It is not necessarily straightforward to organize these publications into well-defined and meaningful categories. Nevertheless, they are grouped here in a way intended to represent important common themes.

a) Experiments Using the CASIA v1 Dataset

One cluster of publications compares different texture filter formulations and presents experimental results on the CASIA v1 dataset. The issue with the CASIA v1 dataset that was mentioned earlier - artificial, circular, constant-intensity pupil regions - does not necessarily compromise the use of this dataset in evaluating the performance of algorithms for texture analysis and matching. However, the small size of the dataset and the many papers in the literature that report near-perfect performance on this dataset make it nearly impossible to use it to document a measurable improvement over the state of the art.

Fatt *et al.* (2009) implemented a fairly typical 1D log-Gabor iris biometric system on a digital signal processor (DSP), and show results on CASIA v1 dataset. Showing the relative speed of software versus DSP implementations of an algorithm is an example of a context where using the CASIA v1 dataset may be reasonable.

b) *"Eigen-iris" Approaches*

One group of papers might be characterized, by analogy to "eigen-faces" in face recognition, as using an "eigen-iris" approach. Chowhan and Sihinde (2009) proposed using PCA for iris recognition, in an eigen-face style of approach. Moravec *et al.* (2009) also used a PCA-based approach, with color images of 128 irises. Chen *et al.* (2009) used 2D PCA and LDA, on UBIRIS images, showing an improvement over PCA or LDA alone. Eskandari and Toygar (2009) explored subpattern-based PCA and modular PCA, achieving performance up to 92% rank-one recognition on the CASIA v3 dataset. Erbilek and Toygar (2009) looked at recognition in the presence of occlusions, comparing holistic versus subpattern based approaches, using PCA and subspace LDA for iris matching, with experiments on the CASIA, UPOL and UBIRIS datasets. (Xu and Guo, 2009) proposed to extract iris features from the normalized iris image using a method that they call complete 2D PCA.

c) *Alternative Texture Filter Formulations*

Many researchers have looked at different mathematical formulations of filters to use in analyzing the iris texture. Patil and Patilkulkarni (2009) used wavelet analysis to create a texture feature vector, with experiments on the CASIA v2 dataset. Velisavljevic (2009) experimented with the use of oriented separable wavelet transforms, or directionlets, using the CASIA v3 dataset, and shows that they can give improved performance for a larger-size binary iris code.

Al-Qunaieer and Ghouti (2009) used quaternion Log-Gabor filters to analyze the texture of images in the UBIRIS color image dataset.

Bodade and Talbar (2009) used a rotated complex wavelet transform in matching iris textures, with experimental results on the UBIRIS dataset, but do not improve recognition performance over the Gabor wavelet. Tajbakhsh *et al.* (2009) use a 2D Discrete Wavelet Transform applied to overlapping 32x32 pixel blocks, and achieve 0.66% EER on the UBIRIS data.

The motivation behind (Miyazawa's, 2000) proposed method is that Daugman-like, feature-based iris recognition algorithms require many parameters, and that their proposed algorithm should be easier to train. For each comparison using the proposed method, they take two images and select a region that is unoccluded in both images. They take the Discrete Fourier Transform of both valid regions, then apply a phase-only correlation (POC) function. The POC function involves a difference between the phase components from both images. They use band-limited POC to avoid information from high-frequency noise. The proposed algorithm requires only two parameters: one representing the effective horizontal bandwidth for recognition, and the other representing the effective vertical bandwidth. They achieve better results using Phase Only Correlation than using Masek's 1D Log-Gabor algorithm.

d) *Alternative Methods of Texture Analysis*

Another group of papers explores texture representation and matching approaches that do not map directly to the typical texture filter framework. Gray level co-occurrence matrices (GLCM) can be used to describe texture in an image. A GLCM is formed by counting the co-occurrences of brightness values of pixel pairs in the image at a certain distance and direction. Chen *et al.* (2009) proposed a modified GLCM based on looking at triples of pixels instead of pairs. They call their modified method a "3D-GLCM", and use it to describe the texture of iris images in the UBIRIS data set. Using equal error rate, the 2D-GLCM method performs better, but for a FAR of 0%, the 3D-GLCM performs better.

Kannavara and Bourbakis (2009) explored using a local-global graph methodology to generate feature vectors, with experiments on color iris images. Sudha *et al.* (2009) computed a local partial Hausdorff distance based on comparing the edge detected images of two irises, obtaining 98% rank-one recognition on a UPOL dataset representing 128 irises. Kyaw (2009) explored using simple statistical features such as mean, median, mode and variance within concentric bands of the iris, but presents no experimental results.

Mehrotra *et al.* (2009) used a Harris corner detector to find interest points, which are paired across images for matching. Tests on Bath, CASIA and IITK datasets indicate that this method does not perform as well as traditional iris code approaches. To avoid aliasing problems from "unwrapping" an iris image, he extracts features from the annular iris image. They use the SURF algorithm (Speeded up Robust Features) to identify rotation-invariant features, and report recognition accuracy above 97% on BATH, CASIA3, and IITK databases.

e) Algorithms ***that Analyze the Iris in Parts***

Several researchers have proposed approaches that analyze the iris region in multiple parts and combine the results. One motivation for this type of approach is to reduce the impact of segmentation errors and noise in the imaging process.

Adam *et al.* (2009) analyzed iris texture in eight sub-regions of the iris and fuse the distances from these local windows, with experiments on data from the CASIA v3 dataset. Bastys *et al.* (2009) divided the iris into sectors and calculate a set number of local extrema in each sector at a number of scales. They achieve perfect separation between genuine and impostor scores for CASIA v1 and CASIA v3 interval, an EER of 0.13% for the CASIA v2 data, and 0.25% for the ICE 2005 data. Eskandari and Toygar (2009) explored sub pattern-based PCA and modular PCA, achieving performance up to 92% rank-one recognition on the CASIA v3 dataset. Lin *et al.* (2009) divided the iris area into four local areas and the face into sixteen local areas in their approach to iris and face multi-biometrics.

Campos *et al.* (2009) proposed an alternative method of feature extraction. They apply histogram equalization and binarization to the unwrapped iris image, and use a Self -Organizing Map neural network to divide the binary image into nodes. From the topological graph of the image, they compute corresponding Voronoi polygons. Next they calculate the mean, variance, and skewness of the image in each polygonal region. They achieve 99.87% correct recognition on the Bath University iris data.

Don *et al.* (2010) presented what is termed a “personalized iris matching strategy”. A weight map is learned for the features in the image of each given iris, based on training images of that iris. This is conceptually similar to the “fragile bits” work of Hollingsworth. This approach is said to be especially useful in the case of poor-quality iris images.

f) Exploiting “Fragile” Bits in the Iris Code

Hollingsworth *et al.* (2009) described the concept of “fragile bits” in the traditional Daugman-style iris code. Bits in the iris code can be fragile due essentially to random variation in the texture filter result, causing them to “flip” between 0 and 1. Recognition performance can be improved by masking an appropriate fraction of the most fragile bits. Dozier *et al.* (2009) used a genetic algorithm to evolve a mask for the iris code that best masks out the “fragile” iris code bits. Hollingsworth *et al.* (2009) described an approach to averaging the iris image through multiple frames of video, prior to generating the iris code, to improve recognition performance. This approach is effectively reducing the fragility of the bits in the iris code. Hollingsworth et al. also describe an approach to using the spatial coincidence of the fragile bits in the iris code to improve recognition performance.

E. **Datasets and Evaluations**

Datasets and evaluations play a large role in biometrics research. The wide spread availability of common datasets has enabled many researchers to enter the field and demonstrate results whose relevance can be more easily understood due to the use of a known dataset. Evaluation programs have given researchers an idea about the current state of the art, and helped to focus and shape research to address the interests of sponsoring agencies.

Proenca *et al.* (2010) described the UBIRIS v2 dataset of visible-light, color iris images, acquired with four to eight meters distance between subject and sensor, and with subjects in motion. The dataset represents 261 subjects, with over 11,000 iris images. The purpose of the dataset is to support research on visible-light iris images acquired under far from ideal imaging conditions.

Johnson *et al.* (2010) described the “Q-FIRE” dataset of face and iris videos. These videos represent variations in focus blur, off-angle gaze and motion blurb, and are acquired at a range of 5 to 25 feet. This dataset is potentially useful for research in iris, face and multi-biometric face + iris.

Fierrez *et al.* (2010) described a multi-biometrics dataset acquired as part of the BioSecurID project. The dataset represents 400 persons, with biometric samples for speech, iris, face, handwriting, fingerprints, palmprint, hand contour geometry and keystroking. The iris images are acquired with an LG Iris Access EOU 3000, and include four samples per eye with subjects not wearing eyeglasses and the presence of contact lenses recorded.

Phillips *et al.* (2009) described the data available in the Multiple Biometrics Grand Challenge (MBGC). The MBGC includes three different challenge problems, one of which involves iris recognition: The Portal Challenge Problem. The goal of the Portal Challenge

Problem is to recognize people from near-infrared and visible-light video as they walk through a portal.

Newton and Phillips (2009) presented a meta-analysis of three iris biometric evaluations: The Independent Testing of Iris Recognition Technology performed by the International Biometric Group, the Iris Recognition Study 2006 conducted by Authenti-Corp, and the Iris Challenge Evaluation 2006 conducted by the National Institute of Standards and Technology. The meta-analysis looks at the variation across the three studies in the false non-match rates reported for a false match rate of 1 in 1,000.

F. Structure and Features of Iris

The iris is a slim, circular structure in the eye that lies between the cornea and the lens of the human eye. The function of iris is to control the diameter and size of the pupil and thus the amount of light reaching the retina (Irsch and Guyton, 2009). The average diameter of the iris is 12mm and the pupil dimension can vary from 10% to 80% of the iris diameter. The color and structure of two irises is genetically linked but the details of patterns are not. They have stable and unique features for personal identification. They are stable with age. The iris begins to form in the third month of gestation and the structures creating its pattern are largely complete by the eighth month, although pigment accretion can continue into the first postnatal years (Kronfeld, 1962). Its complex pattern can contain many distinctive features such as arching ligaments, furrows, ridges, crypts, rings, corona, freckles, and a zigzag collaret (Muron and Pospisil, 2000). The iris is a unique that there are no two irises alike, even twins. These characteristics make it attractive for use as a biometric feature to identify individuals.

G. Iris Recognition

The concept of iris recognition was first proposed by Dr. Frank Burch, 1939 who use iris patterns as a method to recognize an individual (individual biometric: iris scan, 2002). In 1985, Leonard Flom and Aran Safir proposed the concept that no two irises are alike, and awarded a patent for the iris identification concept in 1987 (individual biometric: iris scan, 2002). They approached John Daugman to develop an algorithm to automate identification of human iris. Since then a lot of work has been done in the field of iris recognition and usually recognition algorithms need a combination of various techniques. This work will review different substantial methods.

In 1992, John Daugman was the first to develop the iris identification software. He proposed an Integra-differential operator that finds the circles in image where the intensity is changing most rapidly with respect to changes in the radius. Once located, the iris image is converted to a Cartesian form by projecting it to onto a dimensionless pseudo-polar coordinate system. The features of iris are encoded and a signature is created using a 2-D complex-valued Gabor filter, where the real and imaginary parts of each outcome are assigned a value of 0 or 1 according to whether they are negative or positive. Then the two images are said to be independent if their fractional Hamming distance (HD) is above a certain threshold, about .33. Otherwise, they are a match. Hamming distance (HD) equals number of mismatching bits divided by number of compared bits (Daugman, 1993) (Daugman, 2004).

Wildes *et al.* (1997) proposed recognition system consists of an image acquisition rig (low light video camera, lens, frame grabber, diffuse polarized illuminator, and reticle for operator positioning) interface to a Sun SPARC station20. This system apply Laplacian pyramid and hierarchical gradient-based image registration algorithm in pattern matching to grab the images of iris and make routine procedures of iris recognition system efficient.

Demirel *et al.* (2008) proposed a system for colour iris image using KLD probability density function between input iris and the training set iris image by applying majority voting and feature vector fusion technique. Input iris image is segmented with the help of a manual binary mask with prior knowledge of the maximum and minimum radius of the iris present in the UPOL database. This system is said to have provided 98.44% recognition rate.

Abiyev *et al.* (2008) simulated an iris recognition system using neural networks (NN). Pupil region is detected with the help of a 10x10 rectangular area technique and helps in detecting the iris inner circle. Linear Hough transform is used to remove the effect of eyelids and a thresholding technique is used to remove eyelashes and then the image is enhanced to improve the contrast and brightness. A gradient based learning model is used to classify the pattern which is proposed to provide higher accuracy rate of 99.25%.

Wang *et al.* (2012) designed a recognition system meant for noisy irises using Ad boost and multi orientation 2-d Gabor filters. Iris outer boundary is isolated using a binary segmentation mask. Noises are removed using Circular Gabor and upper and lower eyelids are detected and removed with the help of Random Sample Consensus (RANSAC) technique. Circular integro-differential operator is used to isolate the pupillary boundary. Two types of images are said to be segmented, (i) Accurately Segmented (AS) iris and Inaccurately Segmented (IAS) iris. All the processing is performed separately hereafter for these two types of irises. Rubber sheet model is used to normalize the AS iris whereas a technique called Simplified Rubber sheet model is used for IAS iris.2-d Gabor filters are used to identify both the global and local texture information and then an Adaboost classifier is mused to perform the match score. Experimental results were tested in the database provided by NICE: II competition with 810 images and the system won 2nd place among all 67 participations.

Zhou *et al.* (2013) proposed a new code matching technique. During segmentation stage following steps were followed: (i) to localize pupil boundary histogram analysis and morphological processing were performed, (ii) Outer boundary was considered to have twice the size of pupillary boundary and (iii) To detect and remove upper and lower eyelids, Canny edge operator followed by polynomial curve fitting algorithm were used. After segmenting the iris, it was unwrapped to a rectangular block of fixed size with the help of a convolution operator.1-d Log Gabor filter were applied to extract the texture information and were then store in a k-dimension tree structure. With the help of this k-d tree code matching was performed to find the similarity or dissimilarity match between any two codes.

Song *et al.* (2014) proposed a method based on sparse error correction model, since the noise factors like eyelid and eyelash occlusion and specular and pupil reflections are mainly spatially localized. In this approach training sets of all iris images are considered as a dictionary used for the purpose of classification of simple test sample and finally converted to a huge size dictionary. To make this error correction model efficient, a K-SVD algorithm is implemented. It is proved that the dictionary when learned with help of this algorithm is said to have a better representation. To optimize the system further, three sub-optimal parameters were chosen and were applied to this algorithm and a final SEC –DKSVD training algorithm was implemented.

Sun *et al.* (2014) provided an iris image classification framework based on texture information using a representation technique called Hierarchy Visual Codebook (HVC). HVC is based on two techniques called Vocabulary Tree (VT), and Locality-constrained Linear Coding (LLC), for representing iris textures sparsely. Experimental results show that this method helps in achieving better image classification for iris liveness detection, race classification, and coarse-to-fine iris identification methods. Gabor filter and ordinal filters are used to extract features from the segmented iris images.

H. Age and Gender Prediction

Abbasi *et al.* (2013) critically evaluated iris biometric identification and verification methods. The authors notified that accuracy and performance can be achieved by eliminating inferiority images and using only the quality images and discussed that iris segmentation is a challenging task for off angle images especially noisy and blur images. Iris can be divided into numerous regions and verification of single region can identify individuals. Iris biometrics can be applied to identify soft biometric attributes of an individual such as gender and age group.

a) Age Prediction

A more relevant and earlier analysis of ageing issues in iris biometrics, which can be found in (Fairhurst and Erbilek, 2011) showed that the physical ageing effects on iris are primarily the result of the physiology of pupil dilation mechanisms, with pupil dilation responsiveness decreasing with age. Hence, since pupil dilation is clearly related to the geometric appearance of the pupil and the iris, this suggests that geometric features of the iris may provide useful information for the age prediction task.

Erbilek and Fairhurst (2012) from a different modality have investigated, analysed and documented the effects of different age-band assignment, in order to guide and enhance the management of age-related data and take a step towards the possibility of more objectively determining optimal age-bands which offer a greater possibility of minimising the sensitivity of a system which relies on such information. According to the results presented there, it is suggested that a structure which divides a test population into the three age bands defined by the boundaries ‘<25’, ’25-60’ and’>60’ is one which best reflects age-related trends and provides useful information to support both the analysis and practical management of age-related factors in iris-based biometric systems.

b) *Gender Prediction*

Gender identity is a personal experience of one's own gender. This is generally described as one's private sense of being a man or a woman, consisting primarily of the acceptance of membership into a category of people: male or female. All societies have a set of gender categories that can serve as the basis of the formation of a social identity in relation to other members of society. In most societies, there is a basic division between gender attributes assigned to males and females. In all societies, however, some individuals do not identify with some (or all) of the aspects of gender that are assigned to their biological sex (Carlson and Heth, 2009).

Gender recognition has found its strong applications in fields of authentication, search engine accuracy, demographic data collection, human computer interaction, access control and surveillance, involving frontal facial images. It can also be used as indexing technique to reduce the search space for automatic face recognition. The significance of Gender Recognition and its Classification has been recognized and greatly identified in the field of research and development since the inception of research work on this field at the beginning of 1990s.

Golomb *et al.* (1990) initially used multi -layer neural network to generate a solution to the problem of gender classification. The facial image was manually aligned for the experimental purpose. Around 900 unit images were squeezed into 40 images on which the classification was performed. An error rate of 8.1% was reported. Chu *et al.* (2010) performed yet another experiment on the same problem by considering un-aligned face image, which uses only single face from which various poses were cropped and were combined into a set. The image set were converted into subspaces and correlation coefficient was used to generate the similarity between two subspaces. LU *et al.* (2009) detected different facial regions to accomplish the task of gender classification. Support Vector Machine (SVM) (Gregory and Viola, 2002) classifier was used on face images. They used CAS-PEAL database consisting of grey scale images of size480 × 360. Grey scale image were transformed to a normalized whole face image and normalized internal face image. This method based on fusion of multiple facial regions was able to compensate for facial expressions and lead to better overall performance.

III. RELATED WORKS

Sudha *et al.* (2010) paper presented that the complete IRIS recognition system consists of an automatic segmentation system based on the Hough Transform, and is able to localize the circular IRIS and pupil region, occluding eyelids and eyelashes, and reflections. And (Shirke *et al.,* 2012) show that the Levenstein distance has better discrimination in comparing IRIS codes than the Hamming Distance. But in our work, we are using bit pattern matching technique for matching the IRIS codes. So, our work is improving the previous work done in the IRIS recognition system and also our work shows how we can enhance the security of data by protecting with the unique IRIS code.

Abbasi *et al.* (2013) critically evaluated iris biometric identification and verification methods. The authors notified that accuracy and performance can be achieved by eliminating inferiority images and using only the quality images and discussed that iris segmentation is a challenging task for off angle images especially noisy and blur images. Iris can be divided into numerous regions and verification of single region can identify individuals. Iris biometrics can be applied to identify soft biometric attributes of an individual such as gender, ethnicity and age group.

Fenker *et al.* (2013) discussed methods to eliminate template aging and proposed that multiple iris images should be stored with different dilation value means. Another way is to utilize those sensors that control dilation value. To reduce template aging both aspects (i.e., algorithm for matching templates and sensor use for image acquisition) should be focused.

Table 1: A glance on different iris recognition techniques (Suleiman and Raghav, 2018)

Key Technique	Author Name	Description	Limitations
Multimodel approach on iris recognition	Gil Santos and Edmundo Hoyle (2012)	New fusion of various iris recognition approaches has been suggested utilizing non-perfect visible-wavelength images caught in an unimpeded environment.	Algorithm assessed utilizing noise-free iris images that doesn't give accurate outcomes.
	Tieniu *et. al.*, (2012)	A viable strategy for visible light iris image coordinating by utilizing different attributes of iris along with eye images proposed.	Less efficient
Feature Extraction	Swathi *et. al.*, (2015)	Flexible Iris Recognition was proposed which used Random Transform and Top hat filtering. DWT+DCT were utilized for extracting the iris features.	Computational time is high aimed at real time applications.
Neural Network Approach	Kamal *et. al.*, (2016)	A NN structure was proposed to upgrade iris recognition performance in noisy condition and furthermore to build the recognition rate	Exact Computation time isn't assessed.
	Poornim *et. al.*, (2010)	Fast and Reliable NN structure was presented centered upon the minimum response time for iris localization.	Integro-differential operator suffers from bright spots of the illumination interior to the pupil.
Gabor and KNN for feature extraction and classification	Aworinde and Onifade (2019)	A soft computing model of soft biometric traits for sexual direction and ethnicity identification using Gabor KNN for feature extraction and classification	The dataset used was quiet small to validate the assertion and the work adopted the appearance-based technique, putting just the ridge type and arrangements into consideration.

Table 2: Summary of IRIS Recognition Techniques.

Author Name	Focus Area	Technique Used	Strength	Weakness
Lagree and Bowyer (2011)	Ethnicity and gender prediction based on iris texture.	Six filters are used to create feature vector. Mainly are spot and line detector, thick horizontal line, thin horizontal line, thick vertical lined and thin lines.	Achieved 62 % accuracy in gender prediction with mixed ethnicity.	No considerable Dissimilarity achieved with single ethnicity.
Rose (2010)	Ethnicity prediction based on iris texture.	“Spot” and “line “detector filters are applied to build feature vector	Higher accuracy (up to 90.58%) obtained through SMO by using WEKA	Demographic (local features) ethnicity has not been evaluated.
Sgroi *et. al.* (2013)	Prediction of age group from iris texture	Nine filters are applied to get iris texture features	Aging factor could be investigated	Less accuracy level achieved from iris image.
Xu. X	New approach	Similarity between local & global	Not Independent on	Did not follow the

(2013)	to iris recognition	features of iris image	normalization	traditional recognition method
Lagree and Bowye (2011)	Demographic predictions from iris image	Texture filters spot, Line and Laws structure are used to predict ethnicity and Gender	Demographics attribute can search iris image by criteria, enhance ethnicity prediction	Gender prediction seems less accurate
Latinwo *et. al.* (2018)	Iris Texture Analysis for Ethnicity	Iris texture analysis for ethnicity classification using Self-Organizing Feature Maps was carried out	It has established the strength of SOFM.	The research was not performed on a very large scale of data

IV. Methodology

A. Methods and Materials

This work was conducted using Matlab. Iris recognition has to pass through the Image acquisition, segmentation technique and normalization technique to produce a template to measure the biometric system. Figure 1 shows the gender estimation processing.

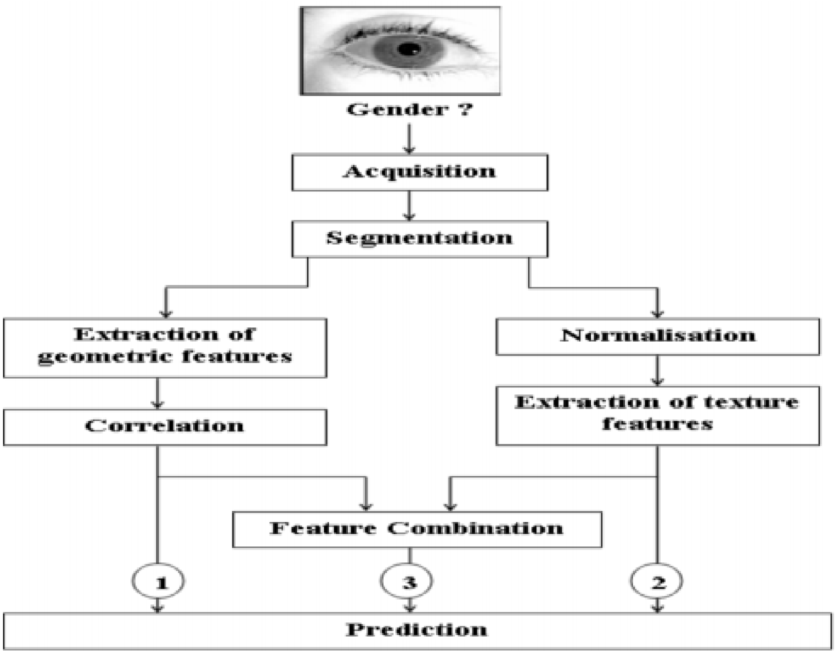

Figure 1: Gender estimation processing

c) Image Acquisition

This step is one of the most important and deciding factors for obtaining a good result. The first phase of our method was collection a large database consisting of several iris images from various individuals. Images in the database was stored in bitmap format on the hard drive of the computer that was used to analyze them. The database was dynamic. The images were captured using a CMITECH IRIS Camera, which have a resolution of 512 dpi to create a meaningful detailed image as shown in figure 3.3. However, to capture the rich details of the iris patterns, a camera at a minimum image resolution of 70 pixels was used. Special cameras with an illumination of 70mm to 90mm wavelengths was used for imaging. Imaging was done with light reflecting at special angles depending on the wavelength so as to capture the rich patterns and striations.

A good and clear image eliminates the process of noise removal and also helps in avoiding errors in calculation. In this case, computational errors are avoided due to absence of reflections, and because the images have been taken from close proximity. Infra-red light was used for illuminating the eye, and hence they do not involve any specular reflections. Some part of the computation which involves removal of errors due to reflections in the image were hence not implemented.

d) ***Segmentation***

In this work, we focus on the Hough Transform iris segmentation technique. In iris segmentation research, accurate boundaries are needed to normalize and match iris image with the database.

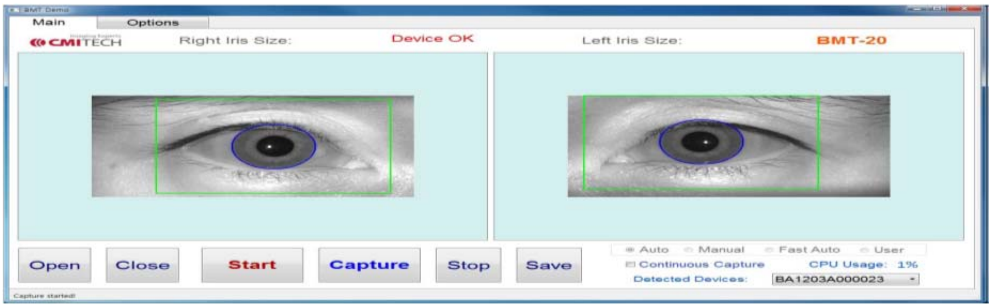

Figure 2: Live Image Display – good eye positioning

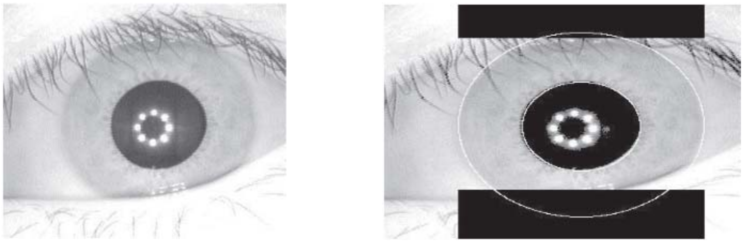

Figure 3(a) Before Figure 3(b) After

Figure 3: Example image before and after apply segmentation technique of pupil and iris localization.

e) ***Image Normalization***

Once the iris region is segmented, the next stage is to normalize this part, to enable generation of the iris code and their comparisons. For normalization of iris regions, a technique based on Daugman's rubber sheet model was employed. The centre of the pupil can be considered as the reference point, and radical vectors pass through the iris region. Virtual circles technique can also be employed.

d) Feature Extraction

Feature extraction is the most important and critical part of the iris recognition system. It is a process of reducing the amount of data required to describe a large set of information present in an iris pattern. The successful recognition rate and reduction of classification time of two iris templates mostly depend on efficient feature extraction technique. The features of the normalized iris template were extracted by applying Principal Component Analysis (PCA) and finding out the feature vector for each iris image.

e) Prediction

In order reliably to evaluate the performance of the classification task, we divide the available samples into person-disjoint testing and training sets. Thus, samples from approximately 60% of the subjects are used as a training set and the remaining subjects' samples are used as a testing set.

f) Classification Using Support Vector Machines (SVMs)

Support vector machines (SVMs) are a group of supervised classification algorithms that be modified to handle various data in order to achieve their aim to separate a binary class by using hyper plane with low misclassification rate. In this stage, multiclass support vector machine was used for matching on two phases (i.e. training phase and test phase).

I. Performance Evaluation

The performance evaluation was done using accuracy, precision, recall (Sensitivity) and false positive rate. There are only 4 cases which are;

- True positive (TP): Prediction is positive and actual value is positive
- True negative (TN): Prediction is negative and actual value is negative
- False positive (FP): Prediction is positive but actual value is negative
- False negative (FN): Prediction is negative but actual value is positive

$$\text{Accuracy} = \frac{\text{Number of correct Prediction (TP + TN)}}{\text{Number of rows in data (TP + FP +FN + TN)}} \times 100$$

$$\text{Precision} = \frac{\text{Prediction actually positive (TP)}}{\text{Total prediction positive (TP + FP)}} \times 100$$

$$\text{Recall} = \frac{\text{Prediction actually positive (TP)}}{\text{Actual positive values in the dataset (TP + FN)}} \times 100$$

$$\text{False Positive Rate} = \frac{\text{Prediction not actually positive (FP)}}{\text{Total prediction negative (FP + TN)}} \times 100$$

V. Results And Discussion

A. Discussion of the Result of the Performance of the Developed Iris Based Age and Gender Detection system

Left and right irises of 190 subjects were captured constituting 1,716 images using CMITECH Iris Camera from students of Ladoke Akintola University of Technology, Ogbomoso, Oyo State. Five Hundred and Seventy (570) left Irises were normalized to a uniform size of 250 by 250 pixels. Three Hundred and Forty-Two (342) irises were used for training while the remaining Two Hundred and Twenty-Eight (228) were used for testing. The iris captured were stored in gray scale format. The application captures the sex and age range. We trained and tested the iris images using MATLAB, figure 4.1 is an interface showing the iris-based age and gender detection system during the implementation stage. Gabor filter algorithm was used due to its effectiveness in pattern recognition. Random sampling cross-validation method was used to test and train our model, where 60% of the data were used for training and 40% of the data were used for testing. We also tested the recognition accuracy, average recognition time of individual iris and performance evaluation of the system, and presented results using graphs and charts, showing the percentage of individual age and their corresponding gender. The performance on trained and tested irises was measured against recognition rate, total training time, false rejection rate and false acceptance rate. The parameters used to measure or evaluate the overall performance of the system are Accuracy, Precision, Recall and False Positive Rate.

If an iris verified is present in a dataset, the result of the fingerprint recognition system is True Positive (TP). If an iris verified is absent in a dataset, the result of the iris recognition system is True Negative (TN). If the iris recognition system confirms the presence of a non-existing iris, the test result is False Positive (FP).

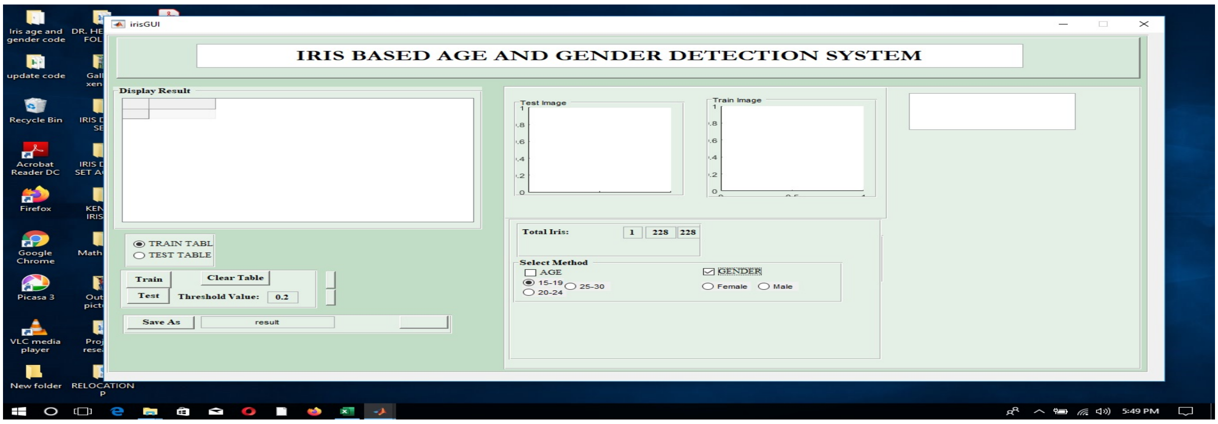

Figure 4.: Interface of the detection system during the implementation stage

If the iris recognition system test suggests that an existing iris is absent in the dataset, the results is False Negative (FN). False Positive Rate (FPR): Proportion between FP and all affected iris images. Recall (Sensitivity) is the ability to identify presence of iris image in the created database, while precision is a valid choice of evaluation metric when we want to be very sure of our prediction.

B. Results for Age Prediction

Table 4.1 describes the result gotten by the iris experiment for predicting age of certain individuals at the age groups of 15-19, 20-24 and 25-30. The results obtained revealed that prediction of the age group 20-24 realized false positive rate of 5.61%, recall of 94.37%, precision of 96.18% and accuracy of 94.38%. It also shows that the computation time ranges between 24.92 to 39.59 seconds. Figure 4.2a and Figure 4.2b shows the scatter diagram of age measurement and age classification region respectively.

C. Results for Gender Prediction

Table 3 presents performance evaluation based on false positive rate, recall, precision and accuracy which were analyzed at threshold values of 0.2, 0.4, 0.6 and 0.75. The results obtained from the table revealed that at threshold value of 0.75, the gender prediction had false positive rate of 2.19%, recall of 92.31%, precision of 96.55% and accuracy of 95.62% at15.21s. The computation time ranged between 15.21 seconds to 15.23 seconds. Figure 5a and Figure 5b shows the scatter diagram of gender measurement and gender classification region respectively.

Table 3: Age prediction using iris

TP	FN	FP	TN	FPR(%)	RECALL(%)	PREC(%)	ACC(%)	TIME (sec)	Age-Group
128	10	6	78	7.14	92.75	95.52	92.79	24.92	15-19
151	9	6	101	5.61	94.37	96.18	94.38	34.4	20-24
33	11	6	31	16.21	75	84.62	79.01	39.59	25-30

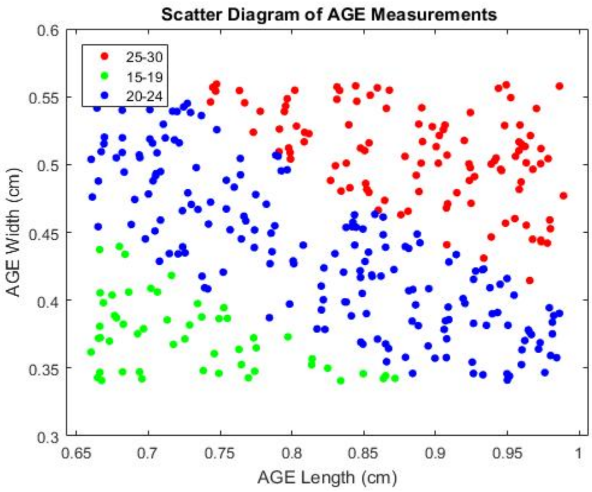

Figure 5a: SVM scatter diagram of age measurements

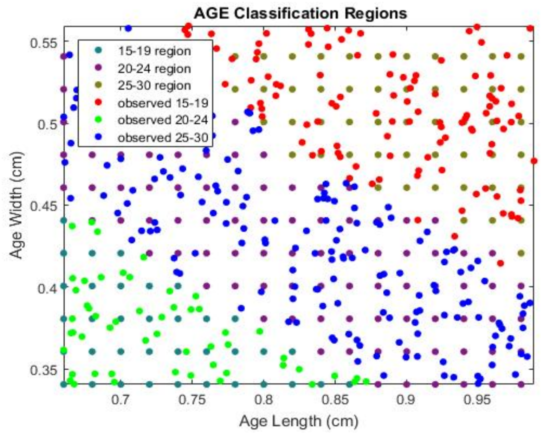

Figure 5b: Scatter diagram for age classification regions

Table 4: Gender prediction using iris

TP	FN	FP	TN	FPR(%)	RECALL(%)	PREC(%)	ACC(%)	TIME (sec)	Threshold
87	4	9	128	6.57	95.60	90.63	94.29	15.23	0.2
85	6	5	132	3.65	93.41	94.44	95.18	15.23	0.4
84	7	4	133	2.92	92.72	95.45	95.30	15.22	0.6
84	7	3	134	2.19	92.31	96.55	95.62	15.21	0.75

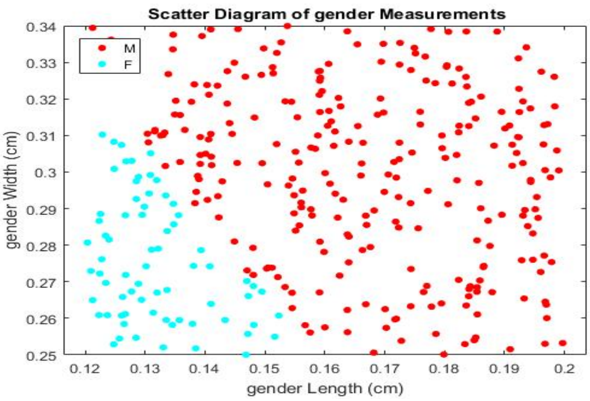

Figure 6a: SVM scatter diagram of gender measurements

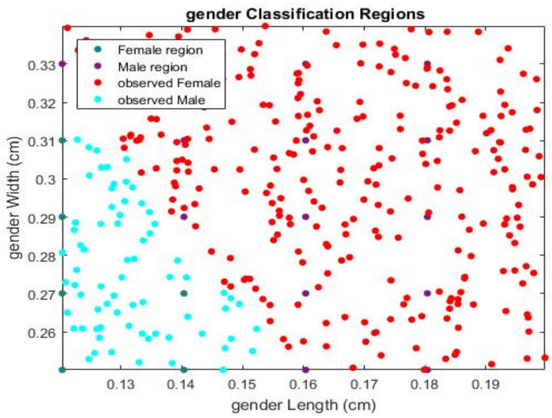

Figure 6b: Scatter diagram for gender classification regions

D. **Discussion of Results**

The results obtained in Table 3 and Table 4 displayed the performance of the techniques employed in this research. The results showed that for gender prediction, there was significant variation in the performance metrics with increase in the threshold value and the best results were obtained at the threshold value of 0.75 across all metrics (False Positive Rate, Recall, Precision and Accuracy). Therefore, the performance of the developed technique is more dependent on the threshold value. Recognition accuracies coupled with False Positive Rate for gender prediction at 0.75 threshold values is 95.62% accuracy at 2.19% FPR.

Figure 6, 7, and 8, is a chart showing accuracy, precision, recall and FPR of age range prediction. Figure 9, 10, 11, 12 and 13 presents the scatter plot metrics.

The age group of 15-19 gave 92.79%, age group of 20-24 had 94.38% and age group of 25-30 gave 79.01% recognition accuracy. Age group of 20-24 has the best results across all metrics as it has the most data fed to the system to train with. Therefore, the more data used in training the system, the better the performance.

Finally, the aforementioned results were determined based on the optimum threshold value which happened to be selected because of its outstanding performance compared to other threshold values.

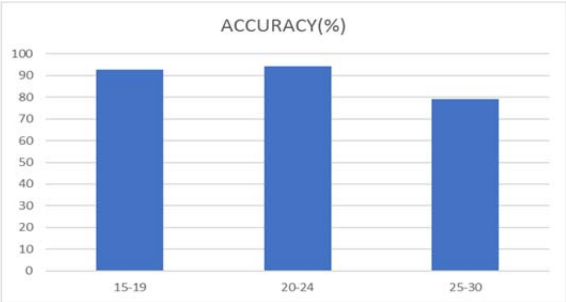

Figure 6: Chart showing Accuracy of age range prediction

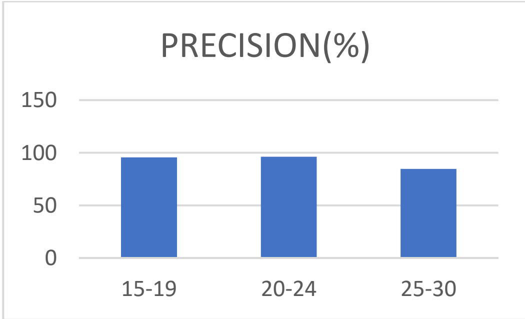

Figure 7: Chart showing Precision of age range prediction

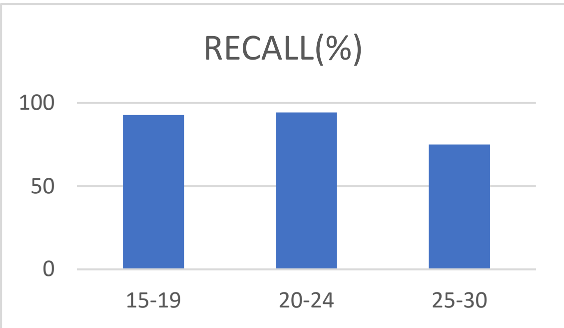

Figure 8: Chart showing Recall of age range prediction

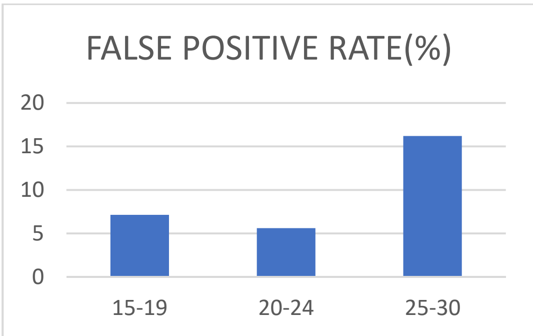

Figure 9: Chart showing False Positive Rate (FPR) of age range prediction

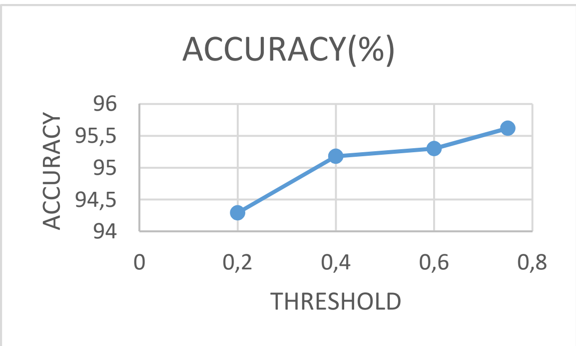

Figure 10: Graph showing Accuracy of gender prediction

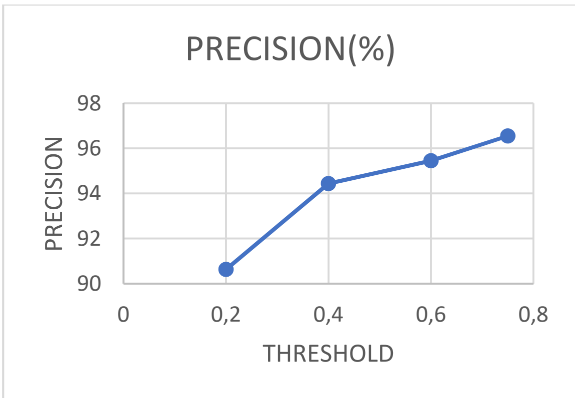

Figure 11: Graph showing Precision of gender prediction

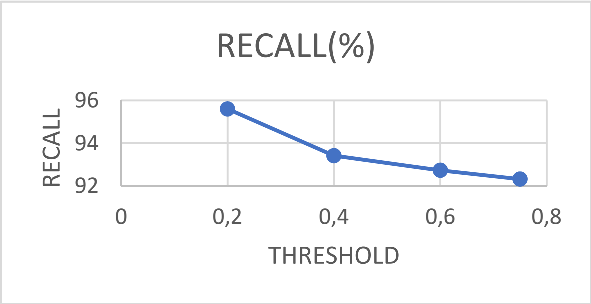

Figure 12: Graph showing Recall of gender prediction

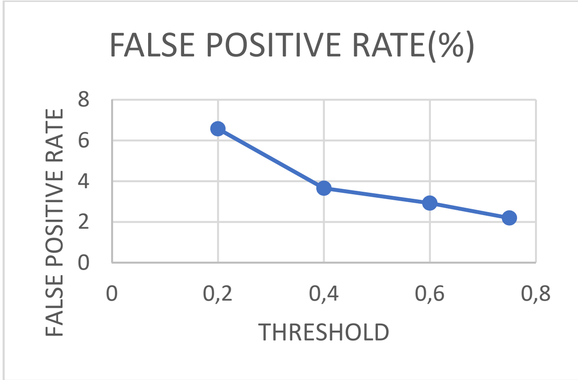

Figure 13: Graph showing False Positive Rate (FPR) of gender prediction

VI. Conclusion And Recommendation

A. Conclusion

Iris recognition has gained huge interest worldwide as an authentic biometric system because of its uniqueness. A collective idea of iris image recognition system is shared in this paper along with the virtues and shortcomings of some approaches for automating iris recognition. The system was divided into different subsystems, namely iris image acquisition, pre-processing, segmentation, normalization, feature extraction, feature selection and classification. It also highlights the significant contribution of researchers in signal and image processing techniques associated with these units of iris recognition systems.

Biometric were captured using CMITECH Iris Camera from students of Ladoke Akintola University of Technology, Ogbomoso, Oyo State. The project substantiated that an individual person’s age and gender can be identified through Iris. This work developed a model that can predict and determine the age and gender of certain individuals in Nigeria using Iris and Matrix Laboratory (MATLAB) Software. The performance of the system was developed using metrics such as Accuracy, Precision and Recall. Age group of 20-24 has the best results across all metrics as it has the most data fed to the system to train with. Therefore, the more data used in training the system, the better the performance. The results showed that for gender prediction, there was significant variation in the performance metrics with increase in the threshold value and the best results were obtained at the threshold value of 0.75 across all metrics

Implementing this approach will in no small measure enhance the effectiveness of security agencies in streamlining the search range of crime perpetrators at crime scenes especially in relation to their age and gender. With a high rate of insurgencies in the world, identifying individuals through inherent attributes (Biometrics) will prevent cases of wrongful arrest and tracking down of evildoers. This system will prevent cases of impersonation when it has to do with accessing some services meant for some particular group of people especially across age line when it borders on, for instance, Local Government Identification process, election activities, quota system when Federal character is being implemented for employment purposes and the likes.

B. Recommendation

Researchers in this line of research can further try some hybrid approaches to improve the performance of the iris recognition system in terms of both increasing accuracy and reducing computation. Deep learning techniques can also be employed for iris image-based biometric systems. As single-core processors are getting upgraded to multi-core processors, researchers can also think on grabbing multiple iris images in a sequence and create techniques to improve the recognition rate. The segmentation in the presence of eyelid and eyelash is still challenging and can be worked upon to improve the automatic segmentation algorithm.

References

[1] Abbasi A., Khan M., and Khan S., (2013). “A Critical Survey of Iris based Recognition Systems” *Middle-East Journal of Scientific Research*, 15(5), 663-668.

[2] Abiyev, Rahib H., and Koray Altunkaya, (2008). "Personal iris recognition using neural network." *Intl. J. Security & its Appl*, 2(2), 41-50.

[3] Adam M., Rossant F., Mikovicova B., and Amiel F., (2009). “Iris identification based on a Local analysis of the iris texture”. Proceedings of 6th *International Symposium on Image and Signal Processing and Analysis* (ISPA 2009), 523-528.

[4] Al-Qunaieer F. S. and Ghouti L., (2009). “Color Iris Recognition Using Hyper complex Gabor Wavelets”. Symposium on Bio-inspired Learning and Intelligent Systems for Security (BLISS’09), 18-19.

[5] Amit S. and James A. L. (1990) “Federated Database System for Managing Distribution of Heterogeneous and Autonomous Databases” *Article in ACM surveys* 22 (3): 183-236. AT&T Cambridge Laboratories, “The Database of Faces.” http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html

[6] Aworinde, H., and Onifade, O.F.W. (2019). A soft computing model of soft biometric traits for Gender and Ethnicity classification. *International Journal of Engineering andManufacturing,* 9(2), 54 -63. https://doi.org/10.5815/ijem.2019.02.05

[7] Baig A., Bouridane A., Kurugollu F., and Qu G., (2009). “Fingerprint-iris fusion based Identification system using a single Hamming distance”. Symposium on Bio-inspired Learning and Intelligent Systems for Security (BLISS ’09), 9-12.

[8] Bastys A., Kranauskas J., and Masiulis R., (2009). “Iris Matching by Local Extremum Points of Multiscale Taylor Expansion,” Advances in Biometrics: Lecture Notes in Computer Science #5558, 1070-1079.

[9] Bodade R.M. and Talbar S.N., (2009). “Shift Invariant Iris Feature Extraction Using Rotated Complex Wavelet and Complex Wavelet for Iris Recognition System.” Seventh *International Conference on Advances in Pattern Recognition* (ICAPR ’09), 449-452.

[10] Boddeti V. N. and Vijaya Kumar B.V.K., (2010). “Extended-Depth-of-Field Iris Recognition Using Unrestored Wavefront-Coded Imagery”. IEEE Transactions on Systems, Man, and Cybernetics -Part A: Systems and Humans 40 (3), 495-508.

[11] Butler A., (2010). “The ACT for Youth Online Presentation: Adolescent Ethnic and Racial Identity Development,” Cornell University.

[12] Campos S., Salas R., Allende H., and Castro C., (2009). “Multimodal Algorithm for Iris Recognition with Local Topological Descriptors”. Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications: Lecture Notes in Computer Science #5856, 766-773.

[13] Carlson N. R. and Heth C. D., "Sensation," in *Carlson, N. R. Carlson, (*2009)

[14] Chen W., Huang R., and Hsieh L., (2009). “Iris Recognition Using 3D Co-occurrence Matrix”.Advances in Biometrics: Lecture Notes in Computer Sci #5558, 1122- 1131.

[15] Chen W.-S., Chuan C.-A., Shih S.-W. and Chang S.-H., (2009). “Iris recognition using 2D LDA + 2 DPCA”. IEEE *International Conference on Acoustics*, Speech and Signal Processing (ICASSP 2009), 869-872.

[16] Chowhan S.S. and Shinde G.N., (2009). “Evaluation of Statistical Feature Encoding Techniques on Iris Images.” 2009 WRI World Congress on Computer Science and Information Engineering, vol. 7, 71-75.

[17] Daugman, J. (1993). High confidence visual recognition of person by a test of statistical independence. IEEE Trans. PAMI (15), pp. 1148-1161.

[18] Daugman, J. (1999). “Countermeasures against subterfuge,” in *Biometrics: Personal Identification in Networked Society*, Jain, Bolle, and Pankanti, Eds.Amsterdam: Kluwer, 1999, pp. 103–121.

[19] Daugman, J. (2004). How iris recognition works. IEEE Trans. Circuits and Syst. For video Tech, 14(2), pp. 21-30.

[20] Daugman, J. and Downing C., (2008). “Effect of Severe Image Compression on Iris Recognition Performance”. IEEE Transactions on Information Forensics and Security 3 (1), 52-61

[21] Demirel, Hasan, and Gholamreza Anbarjafari. (2008). "Iris recognition system using combined colour statistics." In Signal Processing and Information Technology, 2008. ISSPIT 2008. IEEE International Symposium on, pp. 175-179. IEEE.

[22] Dong W., Sun Z. and Tan T., (2009). “A Design of Iris Recognition System at a Distance”. Chinese Conference on Pattern Recognition (CCPR 2009), 1-5.

[23] Dong W., Tan T., and Sun Z., (2010). “Iris Matching Based on Personalized Weight Map”. IEEE Transactions on Pattern Analysis and Machine Intelligence, to appear.

[24] Dozier, G., Frederiksen K., Meeks R., (2009). “Minimizing the number of bits needed for iris recognition via Bit Inconsistency and GRIT”. IEEE Workshop on Computational Intelligence in Biometrics: Theory, Algorithms, and Applications, (CIB 2009), 30-37.

[25] Elmadani A. B., (2010). “Human Authentication Using FingerIris Algorithm Based on Statistical Approach.” Second *International Conference on Networked Digital Technologies* (NDT 2010), 288-296.

[26] Erbilek M. and Fairhurst M., (2012). "A Methodological Framework for Investigating Age Factors on the Performance of Biometric Systems," in *The 14th ACM Workshop on Multimedia and Security*, Coventry, UK.

[27] Erbilek M., and Toygar O., (2009). “Recognizing partially occluded irises using subpattern based approaches”. 24th *International Symposium on Computer and Information Sciences* (ISCIS 2009), 606-610.

[28] Eskandari M. and Toygar O., (2009). “Effect of eyelid and eyelash occlusions on iris images Using Sub-pattern-based approaches”. Fifth *International Conference on Soft Computing*, Computing with Words and Perceptions in System Analysis, Decision and Control, (ICSCCW 2009), 1-4.

[29] Fairhurst M. and Erbilek M., (2011). "Analysis of physical ageing effects in iris biometrics," *Computer Vision, IET,* vol. 5, pp. 358-366.

[30] Fatt R. Y., Tay Y. H. and Mok K. M., (2009). “DSP-Based Implementation and Optimization of an Iris Verification Using Textural Feature”. Sixth *International Conference on a Fuzzy Systems and Knowledge Discovery* (FSKD ’09), vol. 5, 374378.

[31] Fatt R., Haur T.Y. and Mok K. M., (2009). “Iris Verification Algorithm Based on Texture Analysis and its Implementation on DSP”. *International Conference on Signal Acquisition and Processing* (ICSAP 2009), 198-202.

[32] Fierrez J., Galbally J., Ortega-Garcia J., et al., (2010). “BiosecurID: a multimodal biometric database”. Pattern Analysis and Applications 13, 235-246.

[33] Flom L, Safir A (1987) Iris recognition system, U.S. Patent 4 641 349

[34] Gan J.Y. and Liu J.-F., (2009). “Fusion and recognition of face and iris feature based on Wavelet feature and KFDA”. *International Conference on Wavelet Analysis and Pattern Recognition* (ICWAPR 2009), July, 47-50.

[35] Gil Santos and Edmundo Hoyle, (2012). "A fusion approach to unconstrained iris recognition", a Pattern Recognition Letters, 33(8), 984-990.

[36] Golomb BA, Lawrence DT, Sejnowski TJ., (1990). Sexnet: A neural network identifies sex from human faces. Advance in Neural Information Processing Systems; 572-577.

[37] Grabowski K., Sankowski W., Zubert M., and Napieralska M., (2009). “Iris structure acquisition method”. 16th *International Conference Mixed Design of Integrated Circuits and Systems* (MIXDES ’09), 640-643.

[38] Hammerle-Uhl J., Pr¨ahauser C., Starzacher T., and Uhl A., (2009). “Improving Compressed Iris Recognition Accuracy Using JPEG2000 RoI Coding”. Advances in Biometrics: Lecture Notes in Computer Science #5558, 1102-1111.

[39] He Y., Yang H., Hou Y., and He H., (2008). “An Elimination Method of Light Spot Based on Iris Image Fusion”. Communication in Computer and Information Sci 15(12), 415-422.

[40] He Z. and Sun Z. and Tan T. and Qiu X., (2008). “Enhanced Usability of Iris Recognition Via Efficient User Interface and Iris Image Restoration”. 15th IEEE Int. Conf. on Image Processing (ICIP 2008), 261-264.

[41] Hollingsworth K., Bowyer K., and Flynn P., (2009). “Image Averaging for Improved Iris Recognition”. Advances in Biometrics: Lecture Notes in Computer Science #5558, 1112-1121.

[42] Hollingsworth K., Peters T., Bowyer K.W. and Flynn P.J., (2009). “Iris Recognition Using Signal- Level Fusion of Frames From Video”. IEEE Transactions on Information Forensics and Security 4 (4), 837 -848.

[43] Hollingsworth K.P., Bowyer K.W. and Flynn P.J., (2009). “The Best Bits in an Iris Code”. IEEE Transactions on Pattern Analysis and Machine Intelligence 31 (6), 964-973.

[44] Individual Biometric: iris scan. (2002). Retrieved November 22, 2007, from National Center for State Courts: http//ctl.ncsc.dni.us

[45] Irsch, K., & Guyton, D. (2009). Anatomy of Eyes. In Encyclopedia of Biometrics (pp.11-16). New York: Springer.

[46] Johnson P.A., Lopez-Meyer P., Sazonova N., Hua F. and Schuckers S., (2010). “Quality in face and Iris research ensemble (Q-FIRE)”. Fourth IEEE International Conference on Biometrics: Theory Applications and Systems (BTAS 10).

[47] Johnson RG (1991) Can iris patterns be used to identify people. Los Alamos National Laboratory, CA, Chemical and Laser Sciences Division, Rep. LA-12331-PR

[48] Kalka N., Bartlow N. and Cukic B., (2009). “An automated method for predicting iris Segmentation failures”. IEEE 3rd International Conference on Biometrics: Theory, Applications, and Systems (BTAS 09), 28-30, 1 -8.

[49] Kalka N., Zuo J., Schmid N. A. and Cukic B., (2010). “Estimating and Fusing Quality Factors for Iris Biometrics Images”. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans 40 (3), 509-524.

[50] Kamal Hajari, Ujwalla Gawande, and Yogesh Golhar, (2016). "Neural Network Approach to Iris Recognition in Noisy Environment", Procedia Computer, Vol. 78, pp. 675-682.

[51] Kannavara R. and Bourbakis N., (2009). "Iris biometric authentication based on local global graphs: An FPGA implementation". IEEE Symposium on Computational Intelligence for Security and Defense Applications (CISDA 2009), 1-7.

[52] Kronfeld, P. (1962). Gross anatomy and embryology of the eye. In H. Davson, & E. London, in The Eye. UK: Academic.

[53] Kyaw K. S. S., (2009). "Iris Recognition System Using Statistical Features for Biometric".

[54] *International Conference on Electronic Computer Technology*, 554 -556.

[55] Labati R.D., Piuri V. and Scotti F., (2009). "Neural-based iterative approach for iris detection in iris recognition systems". IEEE Symposium on Computational Intelligence for Security and Defense Applications (CISDA 2009), 1-6.

[56] Lagree S. and Bowyer K., (2011). "Predicting Ethnicity and Gender from Iris Texture," *in Proceedings of IEEE International Conference on Technologies for Homeland Security*, Waltham, pp. 440-445.

[57] Latinwo, B. M., Falohun, A.S., Omidiora, E.O., and Makinde, B.O. (2018). Iris Texture Analysis for Ethnicity Classification Using Self-Organizing Feature Maps. *Journal of a Advancesin Mathematics and Computer Science*25(6), 1-10.

[58] Lee Y., Phillips P., and Micheals R., (2009) "An Automated Video-Based System for Iris Recognition". Advances in Biometrics: Lecture Notes #5558,1160-1169.

[59] Li LU, Ziyi XU, Pengfei SHI. (2009). Gender classification of facial images based on multiple facial regions. World Congress on Computer Science and Information Engineering : 48-52.

[60] Lin J., Li J.-P., Lin H. and Ming J., (2009). "Robust person identification with face and iris by modified PUM method". *International Conference on Apperceiving Computing and Intelligence Analysis* (ICACIA 2009), 321 -324.

[61] Liu L., Gu X.-F., Li J.-P., Lin J., Shi J.-X. and Huang Y.-Y., (2009). "Research on data fusion of multiple biometric features". *International Conference on Apperceiving Computing and Intelligence Analysis* (ICACIA 2009), 23-25 Oct., 112 -115.

[62] Matey J.R. and Kennell L.R., (2009). "Iris Recognition -Beyond One Meter, Handbook of`Remote Biometrics.

[63] McCloskey S., Wing Au A. and Jelinek J., (2010). "Iris capture from moving subjects using a Fluttering shutter". Fourth IEEE *International Conference on Biometrics: Theory Applications and Systems* (BTAS 10).

[64] Mehrotra H., Badrinath G.S., Majhi B. and Gupta P., (2009). "An efficient dual stage approach for iris feature extraction using interest point pairing". IEEE Workshop on Computational Intelligence in Biometrics: Theory, Algorithms, and Applications (CIB 2009), 59-62.

[65] Miyazawa K., Ito K., Aoki T. and Kobayashi K., (2008). "An Effective Approach for Iris Recognition Using Phase-Based Image Matching". IEEE Transactions on Pattern Analysis and Machine Intelligence 30 (10), Oct., 1741-1756.

[66] Moravec P., Gajdos P., Snasel V., and Saeed K., (2009). "Normalization Impact on SVD` Based Iris Recognition". *International Conference on Biometrics and Kansei Engineering* (ICBAKE2009), June, 60-64.

[67] Muron, A., & Pospisil, J. (2000). The human iris structure and its usages. Acta Univ. Palacki. Olomuc. Fac. Rerum Nat. Phys., pp. 87–95.

[68] Nandakumar K, Jain AK, Nagar A (2008) Biometric template security. EURASIP J Adv Signal Process 2008(13):113

[69] Newton E.M. and Phillips P.J., (2009). Meta-Analysis of Third-Party Evaluations of Iris Recognition. IEEE Transaction on Systems, Man and Cybernetics part A 39(1), 4-11.

[70] Patil C. M. and Patilkulkarani S., (2009). "Iris Feature Extraction for Personal Identification Using Lifting Wavelet Transform". *International Conference on Advances in Computing, Control, and Telecommunication Technologies* (ACT '09), 764-766.

[71] Phillips P., Flynn P., Beveridge J., Scruggs W., OToole A., Bolme D., Bowyer K., Draper B., Givens G., Lui Y., Sahibzada H., Scallan J., and Weimer S., (2009). "Overview of the Multiple Biometrics Grand Challenge, Advances in Biometrics: Lecture Notes in Computer Science #5558.

[72] Phillips P.J., Scruggs W., O'Toole A., Flynn P., Bowyer K.W., Schott C. and Sharpe M., (2010). "FRVT2006 and ICE 2006 Large-Scale Experimental Results". IEEE Transactions on Pattern Analysis and Machine Intelligence 32 (5), 831-846.

[73] Poornima S., Rajavelu C., and Subramanian S., (2010). "Comparison and a neural network approach for iris localization", Procedia Computer Science Vol. 2, pp. 127-132.

[74] Proenca H., (2008). "Iris Recognition: A Method to Segment Visible Wavelength Iris Images Acquired On-the-Move and At-a-Distance". Advances in Visual Computing: Lecture Notes in Computer Science #5358 32 (8), 731-742.

[75] Proenca H., (2009). “On the feasibility of the visible wavelength, at-a-distance and on-the move iris recognition”. IEEE Workshop on Computational Intelligence in Biometrics: Theory, Algorithms, and Applications (CIB 2009), 9-15.

[76] Proenca H., (2010). “Iris Recognition: On the Segmentation of Degraded Images Acquired in the Visible Wavelength”. IEEE Transactions on Pattern Analysis and Machine Intelligence 32 (8), 1502-1516.

[77] Proenca H., (2010). “Quality Assessment of Degraded Iris Images Acquired in the Visible Wavelength” IEEE Transactions on Information Forensics and Security, to appear.

[78] Proenca H., Filipe S., Santos R., Oliveira J. and Alexandre L., (2010). “The UBIRIS.v2: A Database of Visible Wavelength Images Captured On-The-Move and At-A-Distance”. IEEE Transactions on Pattern Analysis and Machine Intelligence 32 (8),1529-1535.

[79] Qiu X., Sun Z., and Tan T., (2005). "Global Texture Analysis of Iris Images for Ethnic Classification” in *Advances in Biometrics*. vol. 3832, D. Zhang and A. Jain, Eds., ed: Springer Berlin / Heidelberg, , pp. 411-418.

[80] Ren J. and Xie M., (2009). “Evaluation of Iris Images Definition Based on Pupil’s Edge Kurtosis.” 2nd International Congress on Image and Signal Processing, 2009 (CISP’09), 1-4.

[81] Ren J. and Xie M., (2009). “Research on Clarity-Evaluation-Method for Iris Images”. Second *International Conference on Intelligent Computation Technology and Automation* (ICICTA ’09), vol. 1, 682-685.

[82] Ricanek K., (2009). “Dissecting the human identity”. Computer, 96-97.

[83] Rose, A., (2010). IRIS Recognition: The Path Forward. 2(6): 1492-1499. IEEE Computer Society

[84] Ross A., Pasula R. and Hornak L., (2009) “Exploring multispectral iris recognition beyond 900nm”. IEEE 3rd *International Conference on Biometrics*: Theory, Applications, and Systems (BTAS09).

[85] Roy K. and Bhattacharya P., (2009). “Level Set Approaches and Adaptive Asymmetrical SVMs Applied for Non ideal Iris Recognition,” Image Analysis and Recognition: Lecture Notes in Computer Science #5627, 418-428.

[86] Roy K. and Bhattacharya P., (2009). “Iris Recognition in Nonideal Situations,” Information Security: Lecture Notes in Computer Science #5735, 143-150.

[87] Roy K. and Bhattacharya P., (2009). “Nonideal Iris Recognition Using Level Set Approach and Coalitional Game Theory,” Computer Vision Systems: Lecture Notes in Computer Science #5815, 394-402.

[88] Sanderson, S. and J. Erbetta. (2000). “Authentication for Secure Environments based on Iris Scanning Technology”. *IEE Colloquium on Visual Biometrics*.

[89] Sgroi, A., K. Baker, W. Bowyer and P. Flynn, (2013). “The Prediction of Old and Young Subjects from Iris Texture”, In: IAPR International Conference on Biometrics.

[90] Shirke Swati D., Shirke Suvarna D., Gupta, (2012). IRIS Recognition**,** Emerging Trends in Computer Science and Information Technology (ETCSIT2012) Proceedings published in International Journal of Computer Applications (IJCA).

[91] Song, Yun, Wei Cao, and Zunliang He. (2014) "Robust iris recognition using sparse error correction model and discriminative dictionary learning." Neurocomputing137 (2014): 198-204.

[92] Sudha Gupta, (2010). IRIS Recognition System using Biometric Template Matching Technology Asst. Professor, LMIETE, LMISTE,Viral Doshi, Abhinav Jain and Sreeram Iyer, K.J.S.C.E. Mumbai India *International Journal of Computer Applications* (09758887), 1(2).

[93] Sudha N., Puhan N.B., Xia H. and Jiang X., (2009). “Iris recognition on edge maps”. IET Computer Vision 3 (1), 1-7.

[94] Swathi S. Dhage, Sushma Shridhar Hegde, K. Manikantan and S. Ramachandran, (2015). "DWT-based feature extraction and radon transform based contrast enhancement for improved iris recognition", Procedia Computer Science Vol. 45, pp. 256-265,.

[95] Tajbakhsh N., Misaghian K., and Bandari N., (2009). “A Region-Based Iris Feature Extraction Method Based on 2D-Wavelet Transform, Biometric ID Management and Multimodal Communication: Lecture Notes in Computer Science #5707, 301-307.

[96] Thompson J.W. and Flynn P.J., (2010). “A segmentation perturbation method for improved iris recognition”. Fourth IEEE *International Conference on Biometrics: TheoryApplications and Systems* (BTAS 10).

[97] Tieniu Tan, Xiaobo Zhang, Zhenan Sun and Hui Zhang, (2012). "Noisy iris image matching by using multiple cues", Pattern Recognition Letters 33(8), 970-977.

[98] Vatsa M., Singh R., Noore A. and Singh S.K., (2009). "Belief Function Theory Based Biometric Match Score Fusion: Case Studies in Multi-instance and Multi-Unit Iris Verification". Seventh *International Conference on Advances in Pattern Recognition* (ICAPR '09), 433.

[99] Velisavljevic V., (2009). "Low-Complexity Iris Coding and Recognition Based on Direction lets". IEEE Transactions on Information Forensics and Security 4 (3), 410-417.

[100] Wang J., Li Y., Ao X., Wang C. and Zhou J., (2009). "Multi-modal biometric authentication Fusing iris and palmprint based on GMM". IEEE 15th Workshop on Statistical Signal Processing (SSP '09), 349-352.

[101] Wang Q., Zhang X., Li M., Dong X., Zhou Q., and Yin Y., (2012). "Adaboost and multi orientation 2D Gabor-based noisy iris recognition," Pattern Recognition. Lett. 33(8), 978–983S.

[102] Wang Z., Li Q., Niu X. and Busch C., (2009). "Multimodal Biometric Recognition Based on Complex KFDA". Fifth *International Conference on Information Assurance and Security* (IAS'09), vol. 2, 177 -180.

[103] Wang Z.F., Han Q., Li Q., Niu X.M. and Busch C., (2009). "Complex common vector for Multimodal biometric recognition". Electronics Letters 45 (10), 495-496.

[104] Wen-Sheng Chu, Chun-Rong Huang, Chu- Song Chen, (2010). Identifying gender from unaligned facial images by set classification. In Proc. IEEE 20th *International Conference on Pattern Recognition*; 2636–2639.

[105] Wheeler F. W., Amitha Perera A. G., Abramovich G., Yu B. and Tu P. H., (2008). "Stand-off Iris Recognition System". IEEE 2nd *International Conference on Biometrics*: Theory, Applications, and Systems (BTAS 08).

[106] Wibowo E.P. and Maulana W.S., (2009). "Real-Time Iris Recognition System Using a Proposed Method". *International Conference on Signal Processing Systems*, 15-17, 98-102.

[107] Wildes RP (1997) Iris recognition: an emerging biometric technology. Proc. IEEE85(9):1348- 1363

[108] Wildes et al. "Automated, non-invasive iris recognition system and method". U.S. Patent No. 5,572,596 and 5,751,836.

[109] Xu X. and Guo P., (2009). "Iris Feature Extraction Based on the Complete 2 DPCA," Advances in Neural Networks: Lecture Notes in Computer Science #5552, 950-958.

[110] Xu. X., (2013). "A New local and Global Model to Iris Recognition", Advanced Materials Research, pp: 658.

[111] Zhenan Sun; Hui Zhang; Tieniu Tan; Jianyu Wang, (2014). "Iris Image Classification Based on Hierarchical Visual Codebook," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol.36, no.6, pp.1120,1133.Zhou, Steve, and Junping Sun. (2013). "A novel approach for code match in iris recognition." In Computer and Information Science (ICIS), 2013 IEEE/ACIS 12th *International Conference* on, pp. 123-128. IEEE.

[112] Zuo J., Nicolo F. and Schmid N.A., (2010). "Cross spectral iris matching based on predictive image mapping". Fourth IEEE International Conference on Biometrics: Theory Applications and Systems (BTAS 10).