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AGE AND GENDER CLASSIFICATION FROM IRIS IMAGES OF THE EYE USING MACHINE LEARNING TECHNIQUES

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Abstract

The human face stands out as a preferable choice for biometric human authentication, the iris is a secure biometric that contains features with a low forgery rate and is unique to individuals. This paper presents a model for age and gender classification from iris images captured from male and female genders between the ages of 5 and 60 years. The age and gender were grouped as *FemaleYoung, FemaleTeen, FemaleAdult, MaleYoung, MaleTeen, and MaleAdult.* On the six categories, feature extraction was done using a 3D histogram with Principal Component Analysis (PCA) applied for dimension reduction to further reduce duplicated or unwanted features. Next, the Support Vector Machine (SVM) was applied to classify the iris images into the six groups recording various performance values. The 3D histogram with PCA recorded an excellent classification performance accuracy of 99.27% as against the EfficientNet deep learning model which recorded 52.29%. The recommended feature technique can help to adequately classify gender and age from iris images leading to a more robust recognition model. Identifying gender using biometric input will lead to a robust automatic classification devoid of bias and failure.

Keywords: Iris Images, Age and Gender Recognition, 3D Histogram, PCA

1.0 INTRODUCTION

Biometrics are the distinct, measurably identifiable traits that enable the automatic identification of an individual based on their physiological and behavioural characteristics. Physiological parameters include physical characteristics of the body such as fingerprint, face, palm, iris, and DNA. (Kumar et al., 2019). The most reliable biometric identification characteristic is iris because the human iris texture is consistent and cannot be readily altered by environmental factors, it is the basis of the robustness of iris recognition (Alrifaee, 2017). Humans naturally can recognize gender and age by simply looking at the face of the person(s) yet it is an extremely challenging task for the computer. Gender and age recognition is one of the challenging issues of computer vision; to tackle this, a

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computer needs to be programmed in a way it can perform the task of recognition like a human (Irhebhude, Kolawole, & Abdullahi, 2021). Biometric authentication system based on iris image is generally considered more reliable than other systems. The human iris is an annular part of the eye between the pupil and the white sclera and has a peculiar structure and provides many interlacing tiny characteristics such as freckles, coronas, stripes, furrows, crypts etc (Hegazy, 2006). These apparent characteristics, known as iris texture are unique to each individual and the iris pattern's uniqueness shows the individual distinctions existing in the development of the anatomical structure of the body. The visible features generally called the texture of the iris, are special to every person (Tapia & Perez, 2019).

The importance of gender and age recognition cannot be overlooked in human-computer interaction, such as personal identification. It is a useful preprocessing step for face recognition and is also used in television network systems for viewer rating studies. Gender and age-specific computer vision can have further applications in fields such as automated security or surveillance systems, demographic studies, and safe monitoring systems (Rai & Khanna, 2010). Recently, recommendations for nutrition for both healthy and unhealthy people have been made possible based on age and gender (Haseena et al., 2022). The accuracy of age and gender classification depends on feature extraction and classification, with feature extraction serving as a crucial factor for the success of classification. It demands the feature of having the most differentiable characteristics among different classes and retains unaltered characteristics within the same class (Duan et al., 2018).

Several attempts have been made at age and gender recognition using different approaches, such as the development of IoT applications with the use of neuro signal eye images that automatically predict age and gender Kaur et al. (2019). The technique yielded positive results, but, there is need for further enhancement of the system by extracting more robust features. This study proposes a novel gender and age classification method using iris images of the eye.

The proposed technique used principal component analysis (PCA) on extracted 3D-histogram to capture the discriminating features thereby reducing feature dimension with a Support Vector Machine (SVM) for classification.

2. LITERATURE REVIEW

As an iris is well embedded in the human eye, it is thought that the structure of the human iris remains stable throughout a person's life (Hasan & Mstafa, 2022). Some researchers worked on the effect of aging on iris biometrics, Rajput and Sable (2019) proposed a novel method for estimating age group and gender from human iris using deep learning, three statistical features containing age-related information were considered. The input iris images were classified into three age groups (kids, adults, and senior citizens). For experimental purposes, a real-time database of iris images of 213 subjects both male and female was collected. CNN, deep CNN models AlexNet and GoogLeNet (DAGnet) were modified with iris features extracted. The extracted deep-learned features were further classified by a trained multi-class SVM model. The proposed technique achieved 95.34% accuracy for gender estimation and 83.7% for age group classification. This finding supports the hypothesis that the structure of the human iris degrades with age due to eye-related diseases or external factors. This information can be used to classify the age and gender of the iris.

It is, however, noted that the age and gender experiments were conducted differently.

To deal with age and gender classification; Duan et al. (2018) developed a hybrid model that combined Convolutional Neural Networks (CNN) with Extreme Learning Machines (ELM) with facial images. The advantages were maximized by the hybrid architecture: CNN was used to extract features from the input images and the intermediate results were classified by ELM. Experimental results show that the hybrid algorithm improved with an accuracy of 88.2%.

Furthermore, Tapia & Arellano (2019) proposed a method that used modified Binary Statistical Image Features (MBSIF) for gender classification from iris texture images. The algorithm was trained using the GFI-UND database and tested using the GFI-UND-Val and UNAB-Val datasets, the authors explored new filters learning from thirteen natural images using independent component analysis (ICA) obtaining gender classification accuracies of 92.45% for the left iris and 95.45% for the right iris.

Agbo-Ajala and Viriri (2020) proposed the use of CNN architecture to identify the gender and age of human faces in unfiltered real-world settings. The innovative CNN approach was to treat the labels for age and gender as a set of discrete annotations and trained classifiers that anticipated an individual's age category and gender using the OIU-Adience dataset. The CNN design is an end-to-end sequential deep learning architecture that includes feature extraction and classification phases. The network was trained to classify face images into eight age groups, with an accuracy of 83.1%, and for gender into two classes with an accuracy of 96.2%. It is also noted that the age and gender experiments were conducted differently with no clear logic of grouping age into eight.

Khalifa et al. (2019) proposed a robust model for iris gender classification using deep CNN. The authors used a GFI dataset containing 3000 images of left iris images and right iris images of both genders, for the experiment, data augmentation was applied to increase the size of the dataset and avoid overfitting, graph-cut segmentation for partition of an image into different regions and applying the deep CNN for feature extraction and classification achieving an accuracy of 98.88%.

Khan et al. (2021) proposed an authentication method based on gender classification from iris images using SVM. It uses the Zernike, Legendre invariant moments, and gradient-oriented histogram, and has an excellent reaction to prolonged changes. In this study, features were extracted from iris images using invariant moments. Following the extraction of these descriptors, keycode fusion was used to classify the attributes. Using a fused feature vector, SVM was utilized to classify gender. The CVBL dataset was used to evaluate the proposed approach, and the results were compared using Gabor filters and Local Binary Patterns (LBP) to determine the state of the art. The suggested technique achieved an accuracy of 98% in gender classification.

Authors Irhebhude, Kolawole and Abdullahi (2021) worked on a gender recognition system using facial images with high dimensional data. The local dataset and Images of Group (IOG) dataset were used for experimenting, Histogram of Gradient (HOG) and Rotation Invariant Local Binary Pattern (RILBP) were used for feature extraction, with PCA applied to extract the high dimensional features and reduced feature space. PCA was applied to both HOG and RILBP with SVM as the classifier and achieved an accuracy of 99.6% and 99.8% for

PCA for RILBP on Local and IOG datasets respectively.

A proposed method for gender prediction from iris biometrics was put forward by (Costa-Abreu et al., 2015) using dataset 2 (DS2) of the BioSecure Multimodal Database (BMDB). The researchers explored gender prediction using three different approaches which are: the geometric features only, the texture features only and both geometric and texture features extracted from iris images and recorded promising results.

Also, Kuehlkamp et al. (2017) used Multi-Layer Perceptron (MLP) and CNN for gender prediction of iris images. The authors used the "Gender from Iris" (GFI) dataset with a total of three thousand (3000) dataset size and used two main extraction methods which were: data-driven features using raw pixel intensity, and hand-crafted features using Gabor filtering and LBP. They showed hand-crafted features like LBP yield better prediction accuracy (66%) than data-driven features (60%) when using MLP networks. On the other hand, CNNs (using data-driven features) had better performance comparable to MLPs+LBP.

In the work of Tapia et al. (2016), authors explored gender classification using the most relevant features The study found that information is contained in all aspects of the eye and recorded a prediction accuracy of 89% using a subset feature representation.

It is worth noting that not a lot has been done using iris to predict gender and age. It is also clear that the few studies reported showed that experiments were conducted separately for the recognition of gender and age of individual humans. This study is focused on classifying both age and gender from the human iris using PCA on extracted 3D histogram images with SVM used as a classifier.

3. PROPOSED METHODOLOGY

This section describes the processes of data collection and the steps involved in the classification of age and gender from human iris images. The stages of the proposed methodology for age and gender recognition in this paper are as follows:

1. image capturing,
2. feature extraction,
3. dimension reduction,
4. dataset splitting, and
5. classification.

Figure 1 gives the illustration of the different stages with the following subsections describing the various phases.

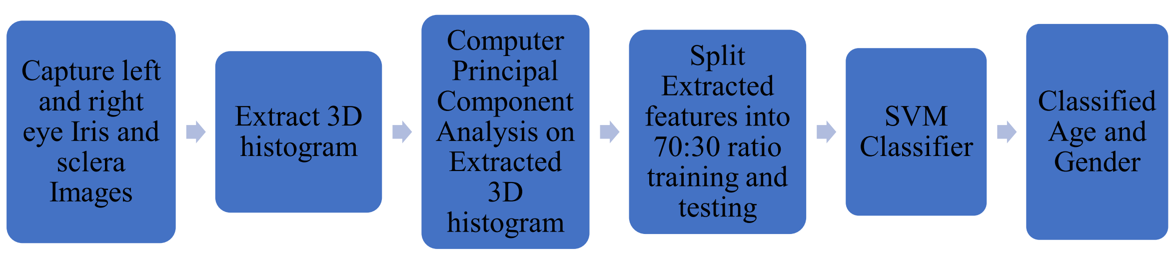

Figure 1: Proposed Methodology for Age and Gender Recognition

3.1 IMAGE CAPTURING/ PREPROCESSING

The first step in implementing the proposed method is image acquisition, which entails taking pictures of the eye images to create the dataset used for the experiment. This was done with a smartphone, an iPhone 11pro max digital camera set to maximum resolution and quality. There were 697 male and female participants in the sample within the age range of 5 and 60. The pictures taken for the study consist of one right and one left eye image for each person. Sample images from the dataset are displayed in Figure 2.

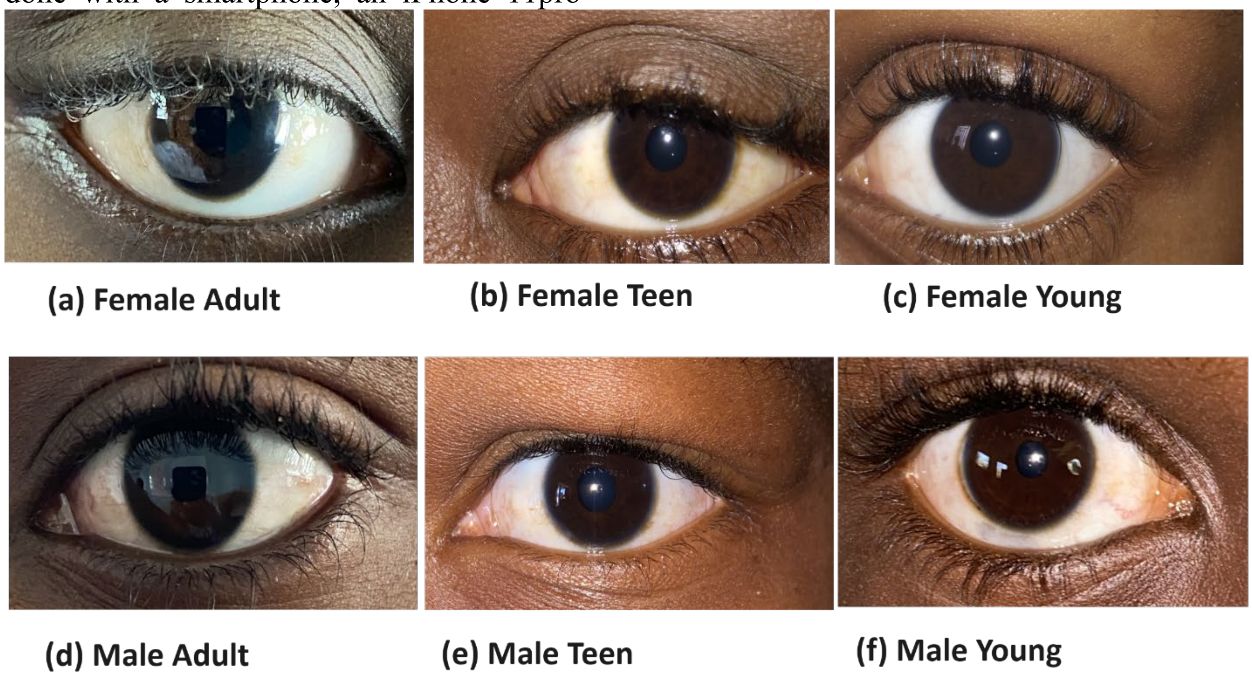

Figure 2: Sample Iris Images of the Selected Categories

Data preprocessing is a crucial step in image recognition, preprocessing aims to improve the image data by suppressing unwanted distortions and enhancing certain image features that are crucial for further processing (Luengo et al., 2020). It covers a wide range of data preparation and reduction methods, data reduction includes; data transformation, integration, cleaning, and normalization, while dimensionality reduction seeks to lower data complexity. Following the implementation of a successful data preprocessing stage, the final dataset obtained can be considered an appropriate source for any experiment (Luengo et al., 2020). Preprocessing in this study involved the resizing of the images to 224 x 224. To preserve the aspect ratio and focus on the region of interest the eye images containing iris and sclera were cropped and resized using Microsoft Paint 3D in Windows 10. The dataset has been divided into 6 age classes and two gender classes (male and female). A description of the dataset and the participant is shown in Table 1.

Table 1: Dataset Description

Class	Number of Images
Female Adult	140
Female Teen	280
Female Young	168
Male Adult	236
Male Teen	362
Male Young	200

3.2 3D HISTOGRAM EXTRACTION

A 3D histogram is a record of colour distribution within an image and it is used to identify common colours or groups of colours in an image (Manek, 2020). The 3D histogram needs three components of colour space RGB which is a three-dimensional colour space with components red, green, and blue which makes up a given colour (Abdelrahim et al., 2011).

The process of extraction in this paper starts with loading the iris images to the RGB color space. To capture the distribution of colors, a 3D histogram is created after the image has been separated into the respective red, green, and channels respectively. The image histogram is calculated on each channel using 64 bins and thereafter concatenated to form the 3D histogram used as features to represent the sclera and iris images. This extracted feature is presented to the SVM classifier for classification into the respective classes.

3.3 PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a dimensionality reduction technique commonly used in various fields, especially computer vision, to transform high-dimensional data into a lower-dimensional representation while preserving as much of the original variance as possible (Hasan & Mstafa, 2022; Irhebhude et al., 2019; Irhebhude, Kolawole, & Abdullahi, 2021; Irhebhude, Kolawole, & Goma, 2021). When applied to the extracted 3D histograms for image classification, it reduces the computational complexity and enhances the discriminative features for classification. PCA has many applications in computer vision, its popularly applied in face recognition (Irhebhude et al., 2019; Irhebhude, Kolawole, & Abdullahi, 2021; Kurita, 2019).

PCA is a dimension reduction method that projects data into low-dimension subspace, the original observations of possible correlated values are transformed into a set of linearly uncorrelated values called principal components (Kherif & Latypova, 2020)

The PCA representation steps are given as follows: The data is organized as a matrix, where each row corresponds to a single 3D histogram, resulting in an $n\,x\,n$ symmetric matrix, where n is the number of dimensions where N is the number of images and M is the matrix size. The covariance matrix of the standardized (Z) data is calculated, and given as shown in equation (1) (Zakaria, 2023)

$$Z = \frac{x - \mu}{\sigma} \quad (1)$$

where x is the data samples, μ is the mean and σ is the standard deviation.

The next step after standardization is a computation of the covariance matrix, this helps to know how variables from the input data vary from the mean (Zakaria, 2023), and the eigenvalues and vectors are computed to identify the PCA. The Eigenvalue is a number that indicates the amount of variance in data with its corresponding eigenvector, the first principal component will be the eigenvector with the highest value (Kherif & Latypova, 2020) and the eigenvectors are sorted based on their corresponding eigenvalues in decreasing order. This indicates the most important components i.e., those that capture the most variance at the beginning. The top k eigenvectors that account for a significant portion of the total variance were chosen and used as the new basis to project the data onto a lower-dimensional space. The covariance matrix ($\sum$)can be represented mathematically as follows;

Let the data to be analyzed by PCA be $Z = [z_1, \dots, z_N]$ with each column having a single observation described by M variables. Sample mean vector $\bar{x}$ is given as equation (2) (Kurita, 2019).

$$\bar{z} = \frac{1}{N}\sum_{i=1}^{N} z_i$$

The covariance matrix is represented in equation (3) (Kurita, 2019)

$$\bar{z} = \frac{1}{N}\sum_{i=1}^{N}(z_i - \bar{z})(z_i - \bar{z})^T = \frac{1}{N}\tilde{Z}\tilde{Z} \qquad (3)$$

where matrix $\tilde{Z}$ is defined as $\tilde{Z} = [z_1 - \tilde{z}, \dots, z_N - \bar{z}]$

In this paper, PCA was extracted on the extracted 3D histogram features from the iris datasets.

3.4 CLASSIFICATION USING SUPPORT VECTOR MACHINE

SVM is a kernel-based classifier that transforms data into high-dimensional feature space where a hyperplane separates the class (Irhebhude, Kolawole, & Bugaje, 2021; Irhebhude et al.; Kaur et al., 2019). This is to discover a classification criterion i.e., a decision function that can correctly separate unknown data. For a two-class data classification, this criterion can be a linear straight line with a maximum distance (margin) from the data of each class. This straight line is also known as a linear hyperplane and is defined as; (Gholami & Fakhari, 2017)

$$w^T x + b = 0 \qquad (1)$$

where w is an n-dimensional vector and b is a biased term

The hyperplane must have the least feasible error in data separation, and it must be the greatest distance from the closest data of each class. Under these conditions, data from each class can only be found on the left (y = 1) or right (y = 1) sides of the hyperplane. To manage the separability of data, two margins can be defined as follows: (Gholami & Fakhari, 2017)

(2)

$$w^T x + b \begin{cases} \geq 1 & for\ y_i = 1 \\ \geq 1 & for\ y_i = -1 \end{cases} \qquad (2)$$

To find the best hyperplane, the distance between the margins should be measured using the following equation (Gholami & Fakhari, 2017);

$$d(w, b; x) = \frac{|(w^T x + b - 1) - (w^T x + b + 1)}{||w||} = \frac{2}{||w||} \qquad (3)$$

The SVM classifier as used in (Irhebhude, Kolawole, & Abdullahi, 2021; Irhebhude, Kolawole, & Bugaje, 2021); Irhebhude et al. (2022) was applied in the experiment to train the model and classify the Iris images into gender and age classes using the reduced-dimensional feature vectors obtained from PCA. The following parameters were adopted and used for the experiment: Linear SVM, multiclass method: one vs one with standardized data. The performance of the experiment was evaluated using the Receiver Operating Characteristics (ROC) curve, True Positive Rate (TPR), False Positive Rate

(FPR), False Discovery Rate (FDR) and Positive Predictive Value (PPV) as reported in (Irhebhude, Kolawole, & Goma, 2021).

4 EXPERIMENTAL RESULTS

The proposed method was tested on self-collected datasets using the proposed model of PCA on a 3D histogram and a comparison was done with the EfficientNet model (Tan & Le, 2019). The results of the two experiments are discussed in this section. For the experiment, 30% of the data was utilized as validation data, and 70% of the data was used for the training. The confusion matrix and ROC curve were used as performance evaluation metrics and are shown in Figures 3 through 8. The figures were used to visualize and explain the findings for both the proposed model and the EfficientNet model. From the experiments conducted, the proposed model had an overall recognition accuracy of 99.27% while the EfficientNet model recorded 52.29%

Figures 3 and 4 show the number of observations from the proposed and EfficientNet models. From the Figures, the blue diagonal cells in the matrix represent the correctly classified class, and the cells also include the number of observed images for each class. The matrix plots plotted the true class against the predicted class, the row denotes the true class and the columns the predicted class. In Figure 3, the *MaleTeen* and *MaleYoung* classes had one and two incorrect observations, respectively, as they were misclassified to belong to the *MaleYoung* category. Despite this, the model did an excellent job of accurately predicting the various classes. This outcome demonstrates the model's excellent ability to identify each class of age and gender from iris images of the eye.

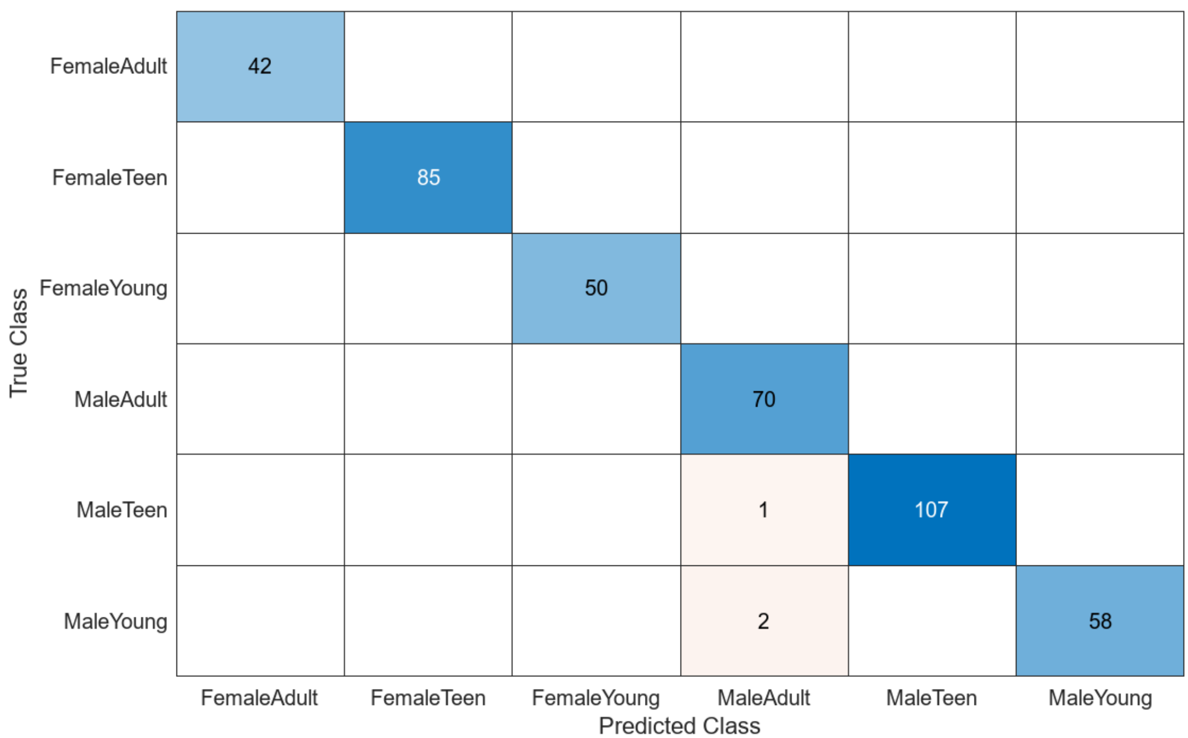

Figure 3: Confusion Matrix for the Proposed Model

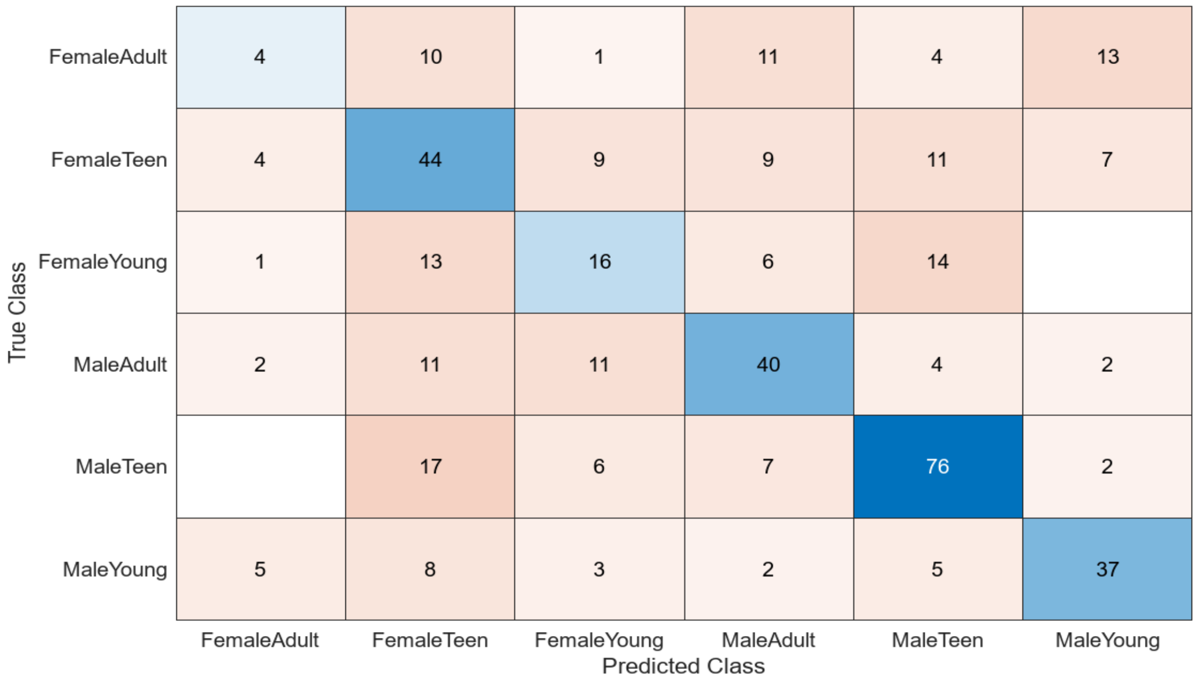

Figure 4:Confusion Matrix for EfficientNet Model (Tan & Le, 2019)

The performance of the EfficientNet model on the dataset is shown in Figure 4, the result of the matrix shows a high number of misclassified images across all the categories. The *FemaleAdult* subject had the lowest number of correctly observed classes (4) with a total of 39 misclassified images. This shows the poor performance of the EfficientNet model to recognize and classify age and gender using the iris images of the eye.

Figures 5 and 6 depict the performance of the models with the confusion matrix of predictive value to investigate the False Discovery Rate (FDR). The Positive Predictive Values (PPV) are the proportion of correctly classified observations per predicted class. The FDR is the proportion of observations that are incorrectly classified per predicted class. The PPV for correctly predicted points in each class is shown in blue, while the FDR is shown in orange for incorrectly predicted points in each class.

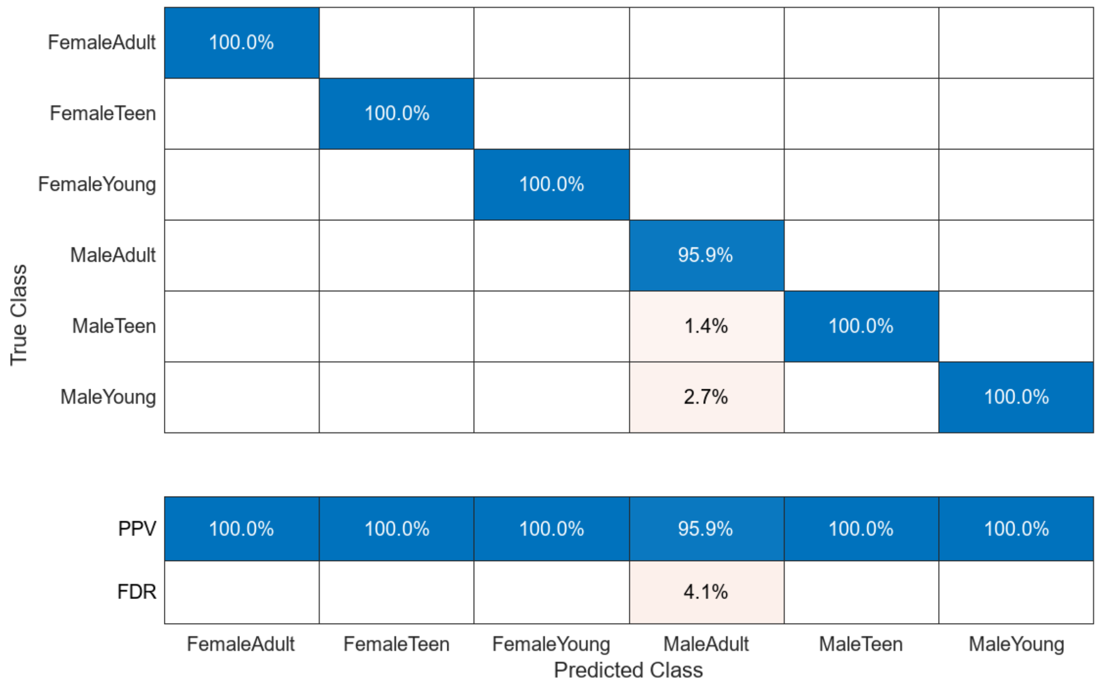

Figure 5: Confusion Matrix of PPV and FDR for the Proposed Model

The confusion matrix in Figure 5 shows the performance of the proposed model using the PPV and FDR. Results clearly show 100% recognition accuracies for all classes except the *MaleAdult* which recorded 95.9% with a margin error of 4.1%. This demonstrates the high-performance rate of the proposed model.

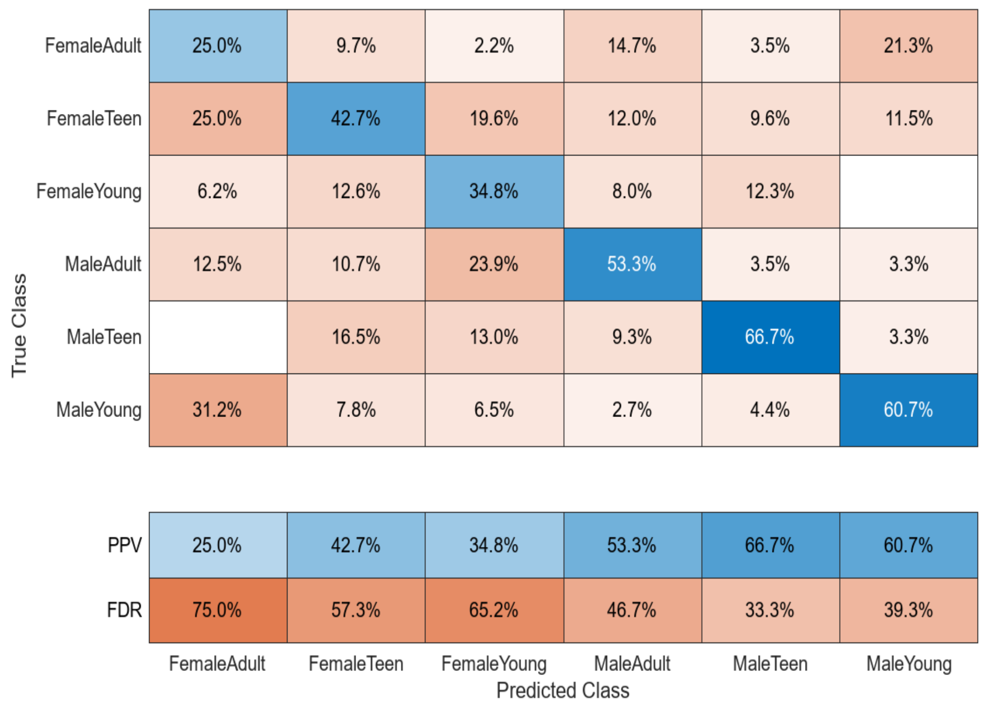

Figure 6: Confusion Matrix of PPV and FDR for the EfficientNet Model

Figure 6 illustrates how well the EfficientNet model performs concerning PPV and FDR. *FemaleAdult* recorded the highest FDR rate of 75.0%. This illustrates the low performance of the EfficientNet model in age and gender classification using iris images of the eye.

To further rate the performance of the proposed and EffecientNet models, Figures 7 and 8 show the performance of the two models. The ROC is produced by plotting the true positive rate (TPR) against the false positive rate (FPR), a curve closer to the upper right of the graph indicates a good performance of the classifier. The area under the curve (AUC) is a measure of how the experiment or test discriminates if a situation or condition is present or not (Hoo et al., 2017).

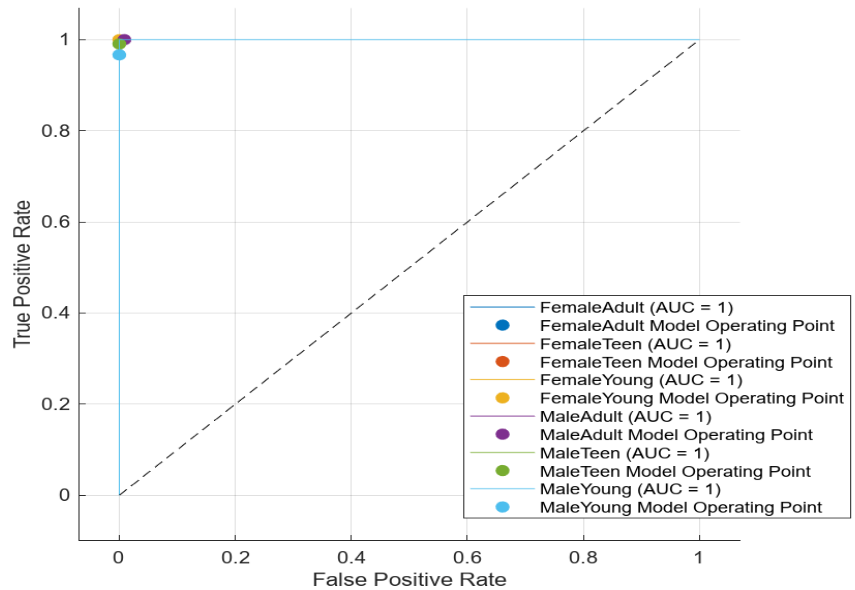

Figure 7: ROC Plot for Proposed Model

Figure 7 displays the result of the proposed model graphically, the ROC gives a perfect curve and AUC value of 1 in all six classes, this shows 100% detection accuracy and represents the model's perfect ability to recognize, and classify age and gender from iris images of the eye.

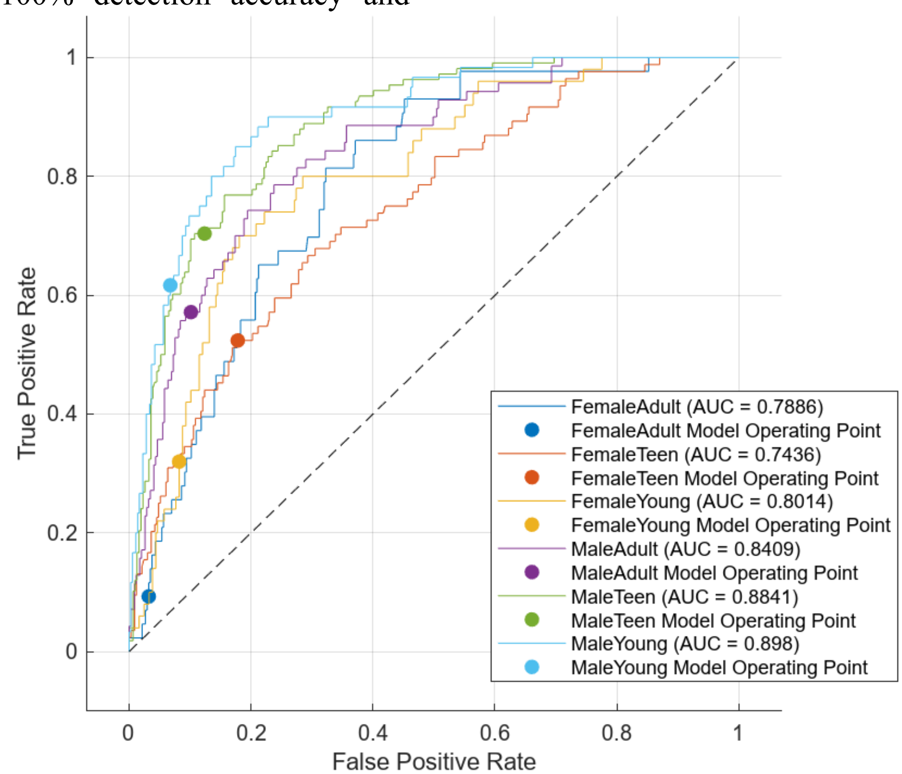

Figure 8: ROC for the EfficientNet Model

The EfficientNet models' performance is shown in Figure 8, from the plot, it is observed that accuracy varies from point to point across the different classes. The *FemaleTeen* and *FemaleAdult* class recorded the lowest AUC values of 0.7436 and 0.7886 respectively, the highest value of 0.898 was recorded by the *MaleTeen* class. The performance shows the ability of the model to classify between the different categories although the accuracy values show fair recognition of 52.29%.

CONCLUSION

In conclusion, this paper proposed a model for age and gender classification using iris images of the eye. A 3D histogram is created after the image has been loaded in RGB color space and PCA is applied to reduce the computational complexity and enhance the discriminative features for classification. SVM was used to train the model and classify the iris images of the eye into gender and age classes with an accuracy of 99.27% compared to the EfficientNet model which recorded 52.29% accuracy. In the future, real-time implementation of the classification using iris images will be considered.

REFERENCES

Abdelrahim, A. S., Abdelrahman, M. A., Mahmoud, A., & Farag, A. A. (2011). Image retrieval based on content and image compression. 2011 International Conference on Multimedia Technology, Hangzhou, China.

Agbo-Ajala, O., & Viriri, S. (2020). Deeply Learned Classifiers for Age and Gender Predictions of Unfiltered Faces. *The Scientific World Journal*, *2020*, 1289408. https://doi.org/10.1155/2020/1289408

Alrifaee, M. M. (2017). A Short Survey of Iris Images Databases. *The International Journal of Multimedia & Its Applications (IJMA) 9*(2), 1-14. https://doi.org/10.5121/ijma.2017.9201

Costa-Abreu, M. D., Fairhurst, M., & Erbilek, M. (2015, 9-11 Sept. 2015). Exploring Gender Prediction from Iris Biometrics. 2015 International Conference of the Biometrics Special Interest Group (BIOSIG),

Duan, M., Li, K., Yang, C., & Li, K. (2018). A hybrid deep learning CNN–ELM for age and gender classification. *Neurocomputing*, *275*, 448-461. https://doi.org/10.1016/j.neucom.2017.08.062

Gholami, R., & Fakhari, N. (2017). Support vector machine: principles, parameters, and applications. In *Handbook of neural computation* (pp. 515-535). Elsevier.

Hasan, B. M. S., & Mstafa, R. (2022). A Study of Gender Classification Techniques Based on Iris Images: A Deep Survey and Analysis. *Science Journal of the University of Zakho*, *10*(4), 222-234.

Haseena, S., Saroja, S., Madavan, R., Karthick, A., Pant, B., & Kifetew, M. (2022). Prediction of the Age and Gender Based on Human Face Images Based on Deep Learning Algorithm. *Computational and Mathematical Methods in Medicine*, *2022*, 1413597. https://doi.org/10.1155/2022/1413597

Hegazy, O. F. (2006). PERSONAL IDENTIFICATION SYSTEM BASED ON HUMAN IRIS RECOGNITION. The International Conference on Electrical Engineering,

Hoo, Z. H., Candlish, J., & Teare, D. (2017). What is an ROC curve? In (Vol. 34, pp. 357-359): BMJ Publishing Group Ltd and the British Association for Accident ….

Irhebhude, M., Celestine, A. U., & Aget, B. J. (2019). Exploring the Efficacy of Face Recognition Algorithm on Different Skin Colors. *IUP Journal of Information Technology*, *15*(1), 34-48.

Irhebhude, M. E., Kolawole, A. O., & Abdullahi, F. (2021). Northern Nigeria Human Age Estimation From Facial Images Using Rotation Invariant Local Binary Pattern Features with Principal Component Analysis. *Egyptian Computer Science Journal*, *45*(1).

Irhebhude, M. E., Kolawole, A. O., & Bugaje, F. B. (2021). Recognition of Mangoes and Oranges Colour and Texture Features and Locality Preserving Projection. *International Journal Of Computing and Digital System*.

Irhebhude, M. E., Kolawole, A. O., & Bugaje, F. B. (2022). Recognition of Ripe, Unripe and Defective Mangoes and Oranges using Image Processing with Colour and Texture Features and Locality Preserving Projection (LoPP) Techniques.

Irhebhude, M. E., Kolawole, A. O., & Goma, H. K. (2021). A gender recognition system using facial images with high dimensional data. *Malaysian Journal of Applied Sciences*, *6*(1), 27-45.

Irhebhude, M. E., Nawahda, A., & Edirisinghe, E. A. View invariant vehicle type recognition and counting system using multiple features.

Kaur, B., Singh, D., & Roy, P. P. (2019). Age and gender classification using brain–computer interface. *Neural Computing and Applications*, *31*(10), 5887-5900. https://doi.org/10.1007/s00521-018-3397-1

Khalifa, N. E. M., Taha, M. H. N., Hassanien, A. E., & Mohamed, H. N. E. T. (2019). Deep Iris: Deep Learning for Gender Classification Through Iris Patterns. *Acta Informatica Medica*, *27*(2), 96. https://doi.org/10.5455/aim.2019.27.96-102

Khan, A. R., Doosti, F., Karimi, M., Harouni, M., Tariq, U., Fati, S. M., & Ali Bahaj, S. (2021). Authentication through gender classification from iris images using support vector machine. *Microsc Res Tech*, *84*(11), 2666-2676. https://doi.org/10.1002/jemt.23816

Kherif, F., & Latypova, A. (2020). Principal component analysis. In *Machine Learning* (pp. 209-225). Elsevier. https://doi.org/10.1016/B978-0-12-815739-8.00012-2

Kuehlkamp, A., Becker, B., & Bowyer, K. (2017). *Gender-from-Iris or Gender-from-Mascara?* 2017 IEEE Winter Conference on Applications of Computer Vision (WACV), https://doi.ieeecomputersociety.org/10.1109/WACV.2017.133

Kumar, S., Singh, S., & Kumar, J. (2019). Gender classification using machine learning with multi-feature method. 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA.

Kurita, T. (2019). Principal Component Analysis (PCA). In *Computer Vision: A Reference Guide* (pp. 1-4). Springer International Publishing. https://doi.org/10.1007/978-3-030-03243-2_649-1

Luengo, J., García-Gil, D., Ramírez-Gallego, S., García, S., & Herrera, F. (2020). Big Data Preprocessing: Enabling Smart Data. *Big Data Preprocessing*.

Manek, G. (2020, 10 November 2023). 3D Histogram Visualizing color spaces. https://www.gauravmanek.com/blog/2011/3d-histogram/#:~:text=With%20all%20this%20knowledge%2C%20we,most%20common%20in%20an%20image .

Rai, P., & Khanna, P. (2010). Gender classification using Radon and Wavelet Transforms. 2010 5th International Conference on Industrial and Information Systems, Mangalore, India.

Rajput, M., & Sable, G. (2019). Deep learning based gender and age estimation from human Iris. Proceedings of the international conference on advances in electronics, electrical & computational intelligence (ICAEEC),

Tan, M., & Le, Q. (2019). *EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks*

Proceedings of the 36th International Conference on Machine Learning, Proceedings of Machine Learning Research. https://proceedings.mlr.press/v97/tan19a.html

Tapia, J. E., & Perez, C. A. (2019). Gender classification from NIR images by using quadrature encoding filters of the most relevant features. *IEEE Access*, *7*, 29114-29127. https://doi.org/10.1109/ACCESS.2019.2902470

Tapia, J. E., Pérez, C. A., & Bowyer, K. (2016). Gender Classification From the Same Iris Code Used for Recognition. *IEEE Transactions on Information Forensics and Security*, *11*, 1760-1770.

Zakaria, J. (2023). *A Step-by-Step Explanation of Principal Component Analysis (PCA)*. Retrieved 19 NOvember 2023 from https://builtin.com/data-science/step-step-explanation-principal-component-analysis

