

A Deep Learning-Based Model for Detecting Underage Voters in the Nigerian Voter Database

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Abstract— The persistent issue of underage voting in Nigeria is examined using deep learning. This study applies Vision Transformer (ViT) architectures for facial analysis-based detection of underage voters. Despite constitutional restrictions and biometric voter registration, minors continue participating in elections. This undermines both electoral integrity and democratic legitimacy. A dataset of 2,892 augmented facial images, from 897 originals, was compiled. These images were categorized as Underage, Middle-aged, and Adult. The dataset was used to train and evaluate the ViT model. The model achieved 79% overall accuracy. It performed particularly well in identifying the underage class (precision: 0.80, recall: 0.79, F1-score: 0.79). Performance was lower for the middle-aged group, likely due to subtle facial distinctions between late adolescents and young adults. These findings highlight both the promise and limits of deep learning for automated age estimation in elections. The results indicate it is feasible to integrate AI-based facial analysis into electoral verification systems to improve transparency. The study also emphasizes the need for larger and more diverse datasets to enhance model generalizability.

Keywords— Underage Voting, Deep Learning, Age Estimation, Facial Analysis, INEC Biometrics

I. INTRODUCTION

The cornerstone of democracy is free and fair elections, which are considered essential for democratic consolidation [1]. Allowing minors to vote introduces votes from individuals who are legally ineligible, which can directly affect election outcomes by potentially altering results and indirectly diminish public trust by creating perceptions or realities of unlawful voting [2][3]. In Nigeria, although the constitution prohibits under-18 voting, underage registration persists, raising specific concerns about the credibility of electoral outcomes and fueling doubts about the legitimacy of the electoral process [4].

Since 1999, when civilian rule returned, the Independent National Electoral Commission (INEC) has progressively adopted biometric technologies for voter registration security. The transition from optical mark recognition to digital fingerprint and photograph capture was an initial advancement that enabled the detection of duplicate votes in real time at polling units [5]. INEC introduced the Biometric Voter Registration (BVR) system nationwide, which uses fingerprint scanning and incorporates Advanced Fingerprint Identification System (AFIS) algorithms to address multiple registrations. Prior to the 2023 general election, INEC used new technology integrating fingerprint and face recognition to authenticate voters in real time [3]. An early study in Nigeria proposed using an artificial neural network (ANN) for a biometric system to verify voters' ages, suggesting the approach was effective, but it was not adopted by INEC [4]. However, current systems are limited in authenticating the age of registrants. The existing biometric infrastructure was primarily developed for identification verification rather than age estimation, creating a gap in assessing voter eligibility.

This study addresses the gap by using a Vision Transformer (ViT) model, a type of deep learning neural network designed to analyze visual data, which has been trained on a wide range of facial images. The objective is to evaluate how effectively the algorithm can categorize voters into age-based groups that determine voting eligibility, with an emphasis on identifying individuals who do not meet the minimum legal voting age. This study seeks to contribute to improvements in election processes in Nigeria by addressing technical and procedural limitations in existing voter verification technologies.

II. RELATED WORKS

In a study on age detection in Nigeria, [4] used iris biometrics and a four-layer deep neural network to address underage voting. They cropped and processed high-resolution iris images, then fed them into the neural network. This method proved more accurate and harder to tamper with than using facial photos. Out of 240 photos, the system correctly classified 215 eligible and 18 ineligible voters, achieving 97.1% accuracy with a few mistakes. Though limited by a small dataset and deployment challenges in remote areas, this research highlights the strength of biometric systems for election integrity and related uses.

A review [6] compared methods for few-shot image classification, focusing on how well each worked. On one dataset, the most recent methods achieved over 98% accuracy for both 1-shot and 5-shot tests, showing that this test is well-studied. On another dataset, certain models like DeepBDC scored 67.8%, and other methods achieved similar results. The review found that metric-based few-shot methods are often the best choice.

A back propagation neural network-based face-based age estimate system with preprocessing, feature extraction, and classification is described by [7]. Viola Jones clipped 40x40 grayscale FGNET facial photographs. Principal Component Analysis was used to choose the top 40 eigenvectors indicating critical face traits for a Back Propagation Neural Network with 40 input neurons, 50 hidden neurons, and one output to divide people into eight age groups. The model outperformed AGES, BIF, WAS, and LARR with 82.2 percent accuracy and 3.88 years of mean absolute error after training on 450 photos and testing on 180. African facial databases are infrequently used in global research, making this endeavor vital. The model struggles with mid-age groups with less facial texture change due to its tiny dataset. PCA and neural networks age African faces.

[8] introduced CSMAE deep learning in Pattern Recognition Letters. Facial picture maturity prediction. To reduce class variation, the model aligns samples with class average during feature learning. CSMAE surpassed Face++ and VGG Face in binary categorization of adults versus youngsters on the Multi Ethnicity Dataset and MORPH Album II, scoring 92.09 percent and 73.13 percent, respectively. Used ROC, McNemar, and accuracy tests. The study addresses a gap by determining legal adulthood, not subjective age. Because modest physiological differences decreased accuracy near 16–19 years, the model performed better on male faces and indicated gender bias. Dataset quirks limited generalization. Although limited, the CSMAE model and Multi Resolution Face Dataset are noteworthy, and the authors advocate using more demographic data and multi-label age classification in future studies.

[9] Proposed in their study the utilization of Deep Convolutional Neural Network for Automatic Classification of age for voters, by exploring the usage of VGG16 deep convolutional neural deep network to automate age verification in Nigeria's electoral process. Utilizing 11,779 images of faces that are obtained from the INEC database, the model classified individuals into underage (below 18) and valid (18 and above) voter groups. Implemented in PyTorch, the study tested Adam and SGD optimizers, with Adam achieving the highest accuracy of 79.79 percent but showing signs of overfitting, while SGD delivered slightly lower accuracy of 77.67 percent with better generalization. Cross entropy loss and minimal image preprocessing highlighted the model's resilience to factors like lighting and pose variations. Despite these results, the binary classification oversimplifies the age estimation task and may benefit from a multi class or regression approach. The lack of image preprocessing, although intentional, could limit effectiveness in real world scenarios. Applying artificial intelligence to uphold electoral integrity in developing countries is a gap that this study addresses, being the first deep learning initiative for civic verification in Nigeria, and proposes future enhancements through ensemble or hybrid classifiers to improve generalizability across diverse populations.

[10] Improved gender and age categorization with a deep random forest model and deep learning. A Multi Instance Multi Scale Fusion Learning Network based on MobileNetV3 extracts features and a gender-aligned conditional deep random forest model estimates age depending on gender prediction. The model beat CNN, SVM, and CNN ELM models on MORPH II with 99.6% gender and 96.14% age group categorization and 93.48% and 63.72% on Adience. Although successful, the model does not account for race, facial expression, or posture and uses a lot of computer resources due to its multi-instance structure. It addresses a gap in simultaneous age and gender prediction by developing a scalable, task-dependent framework that increases generalizability and shows how conditional and multi-task learning manages subject variability.

[11] Estimated human age from facial photos using deep convolutional neural networks, and Transfer Learning to predict human age from facial photographs. To reduce overfitting, we replaced and trained each model's final fully connected layers using regression, data augmentation, dropout regularization, and early stopping. The African facial dataset of Hausa-ethnic CASIA and UTKFace were used to evaluate the models, employing mean absolute error (MAE) and R-squared (R^2) as performance metrics. MobileNet had the best CASIA MAE of 1.10, followed by VGG16 with 1.75 on UTK, outperforming several state-of-the-art algorithms. Transfer learning addresses context-specific issues like Nigerian underage voting identification utilizing African facial data. Age imbalance and lack of real-time video or CCTV testing limit CASIA. Despite these limitations, fine-tuned CNNs may

accurately perform age regression on African datasets for digital government, healthcare, and security.

III. METHODOLOGY

The methodology for implementing the model to detect underage voters is structured into five key stages as shown in figure 1.

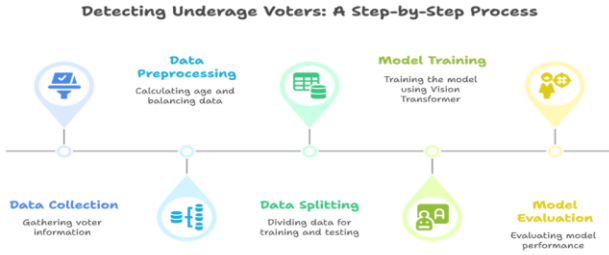


Figure 1: Architectural framework for detecting underage voters

A. Dataset Collection and Annotation

For the purpose of this study, data were predominantly acquired from primary sources through the engagement of randomly selected individuals aged 12 years and older. These individuals were selected from various locations in Nigeria and provided their informed consent. To achieve the study's objectives, the goal was to compile a dataset pertinent to the detection of voter eligibility. Specifically, the demographic data collected, which encompassed name, age, and facial characteristics, was meticulously organized to align with the format employed by the Independent National Electoral Commission (INEC) and subsequently stored in a CSV (comma-separated values) format for processing. In addition to the field data, passport-style facial images were obtained from publicly accessible online platforms (such as shutterstock.com and stock.adobe.com), encompassing representations of both underage individuals (those below 18 years) and individuals of legal voting age (18 years and older). To ensure robust representation, these images were curated to include a spectrum of age groups and were utilized exclusively for academic and research purposes, thereby upholding rigorous ethical standards. Building upon this integrated dataset, it was systematically annotated and classified into three principal categories, namely: underage, middle-aged, and adult, to facilitate the development and training of the machine learning model intended to discern underage voters based on facial characteristics. Consequently, a total of eight hundred and ninety seven (897) data was collected, comprised of two hundred and forty six (246) underage voters (below 18), three hundred and forty nine (349) legitimate voters categorized as middle age (18 to 30), and three hundred and two (302) as

adult (31 and above). For illustration, a snippet of the collected dataset is presented in Figure 2, while samples of both underage voters and legitimate voting age are depicted in Figure 3.

VoterID	FirstName	LastName	DateOfBirth	Gender	StateOfResidence	StateOfOrigin	LGA	Ward	PollingUnit
VIN00001	Temitope	Weich	17/12/1998	Female	Lagos	Ogun	Ibeja	Ward 3	PU-19
VIN00002	Sarah	Emeka	27/10/1993	Female	Anambra	Imo	Newai North	Ward 2	PU-17
VIN00003	Oluwafemiola	Sharp	28/11/1990	Female	Lagos	Ogun	Surulere	Ward 5	PU-28
VIN00004	Ebi	Navaro	27/06/1998	Female	Rivers	Bayelsa	Port Harcourt	Ward 5	PU-20
VIN00005	Funke	Goodman	30/10/2000	Female	Lagos	Ogun	Ibeja	Ward 1	PU-27
VIN00006	Tamuno	Paul	21/05/2003	Female	Rivers	Bayelsa	Port Harcourt	Ward 3	PU-1
VIN00007	Adedira	Turner	31/07/1977	Female	Lagos	Ogun	Ibeja	Ward 2	PU-17
VIN00008	Yelande	Williams	25/01/1977	Female	Oyo	ENI	Ibarga East	Ward 4	PU-28

Figure 2: Snippet of the compiled CSV dataset containing voter registration details.



(a) Under age (b) Middle-aged (c) Adult

Figure 3: Samples of passport photographs of voters who fall within the legitimate and illegitimate voters

B. Data Preprocessing

In this stage, the dataset underwent an initial process of cleansing and standardization to ensure uniformity across all data entries. We computed each individual's age using the formula (Date of Registration – Date of Birth) and classified them into three categories—underage, middle-aged, and adult—according to defined age ranges relevant to voting demographics. All passport images were resized to 224×224 pixels for consistency. These images were then normalized to the [0, 1] range before being used by the network. We applied data augmentation techniques such as random horizontal flip, random rotation, and color transformation. This artificially expanded the dataset from eight hundred and ninety seven (897) to two thousand eight hundred and ninety two (2,892) entries to prevent overfitting and improve model generalization. To address class imbalance, especially between underage and eligible voter categories, we used the Synthetic Minority Over-sampling Technique (SMOTE). This involved making synthetic examples for the minority class using an oversampling ratio of 1:1 between minority and majority classes, and 5 nearest neighbors for interpolation. This process helped ensure that samples were more evenly distributed and improved the model's ability to classify correctly. The statistics of the dataset after augmentation are summarized in Table 1.

Table 1: Statistics of the Dataset after Augmentation

Age Distribution	Adult	1232
	Middle-aged	1216
	Underage	444
Mean Age	30.13	
Gender Distribution	Male	1780
	Female	1112
Image Resolution	224×224px	

C. Data Splitting

We used the Pareto principle, also known as the 80/20 rule, to split the dataset into two parts. We set aside 80% of the information for training so the model could learn the patterns and traits of underage voters. The last 20% was used for testing. This gave us an unbiased view of the model’s performance on data it had not seen before. This approach ensures a balanced trade-off between learning depth and validation accuracy.

D. Model Development and Training

Vision Transformers (ViTs) are deep learning models that use the transformer architecture from natural language processing (NLP) to recognize images. ViT divides an image into fixed-size patches and considers each patch as a token in a sequence to extract spatial information instead of utilizing convolutional layers like CNNs. The model captures complex visual patterns and relationships across the scene by processing these patches using self-attention mechanisms [12].

(ViT) architecture was implemented to classify voter images into specific age groups, with the goal of identifying individuals who may be below the legal voting age. The dataset was preprocessed to guarantee consistency in image quality and format, and labels were assigned based on verified age data making it suitable for training the ViT model. The ViT architecture adopted in this study was ViT-B/16, which consists of 12 transformer encoder layers, each with a 768-dimensional hidden size, 12 attention heads, and a patch size of 16×16. The model was initialized with ImageNet-pretrained weights to leverage transfer learning for age group classification. The model was fine-tuned using the Adam optimizer with a learning rate of 1×10^{-4} , a batch size of 16, and trained for 5 epochs. ViT was chosen due to its strong image classification task performance, particularly in capturing complex visual patterns. The model was trained on the prepared dataset, learning to associate facial features with age categories, which served as the foundation for detecting potential underage voters.

E. Model Evaluation

A standard and task-specific metrics to evaluate the Vision Transformer (ViT) model during the model review phase. This was done to provide a full picture of how well it worked at finding underage voters. Initially, the model’s learning behavior was monitored using four key metrics: The accuracy and loss of training, as well as the accuracy and loss of validation. The training accuracy is the number of properly predicated samples divided by the total number of samples in the training set. It shows how well the model fits the training data. It is given by the formula in equation 1.

$$Accuracy = \frac{NumberofCorrectPredictions}{TotalNumberofPredictions} \times 100 \quad (1)$$

On the other hand, training loss indicates you how incorrect the model’s predictions were on the training data. We employed the cross-entropy loss function for this classification job, which is shown in equation 2.

$$Loss = -\sum_{i=1}^N y_i \log(\hat{y}_i) \quad (2)$$

where y_i is the true label and \hat{y}_i is the predicted probability for class i , and N is the number of classes.

To ensure the model generalized well beyond the training data, validation accuracy and validation loss were also tracked using the reserved validation set (20% of the dataset). These metrics were computed in the same way as for the training data but applied to unseen samples. A consistent gap between training and validation accuracy, or a rising validation loss while training loss decreases, would suggest overfitting. Monitoring these metrics over multiple epochs provided insight into how well the model learned relevant features and how reliably it could detect underage voters in new, unseen data.

We additionally examined the model’s precision, recall, and F1-score to get a better idea of how well it classified voters, especially how well it demonstrated the difference between underage and eligible voters. A ccuracy is the percentage of true positives out of all anticipated positives, recall measures the percentage of true positives found out of all real positives, and the F1-score is the harmonic mean of accuracy and recall, which balances both concerns as shown in equation 3

$$Precision = \frac{TP}{FP+TP} \quad (3)$$

The formula for Recall is shown in equation 4.

$$Recall = \frac{TP}{FN+TP} \quad (4)$$

While the F1-score is calculated as presented in equation 5.

$$F1score = \frac{2*Precision*Recall}{Precision+Recall} \quad (5)$$

These additional metrics are critical in a real-world context where false positives (misclassifying eligible voters as underage) and false negatives (failing to identify underage voters) carry different implications. Together, these evaluation criteria offered a robust framework for assessing the model's reliability and practical application. The training and evaluation processes were managed using the Hugging Face Trainer API.

IV. RESULT AND DISCUSSION

This section presents the analysis and evaluation of performance of the proposed method. The experimental dataset contained two thousand, eight hundred and ninety two (2892) samples and was gathered carefully using the real voters register as guide to obtain relevant information. The dataset was categorized into three groups namely; Adult (consist of ages from 31 years and above), Middle-aged (between 30-18 years) and Underage (below 18 years). Each sample has an image assigned with information and label based on its category.

In this study, the dataset was divided in a ratio of 80-20, (80%) for training and (20%) for the testing of the model. The data was randomly selected and was evaluated on the testing set to obtain prediction results. The model's performance was evaluated using key metrics like precision, recall, f1-score, and support for each class, along with overall accuracy, macro average, and weighted average which reveals how well the model predicted each category as shown in figure 4.

	precision	recall	f1-score	support
Underage	0.8010	0.7887	0.7948	194
Middleage	0.7677	0.7876	0.7775	193
Adult	0.8010	0.7927	0.7969	193
accuracy			0.7897	580
macro avg	0.7899	0.7897	0.7897	580
weighted avg	0.7899	0.7897	0.7897	580

Figure 4: Model Performance Evaluation Performance by Class

A. Adult Class

When the model predicted an individual was "Adult," it was correct 80% (0.80 precision) of the time. This indicates a moderate level of true positive predictions among all positive predictions for this class. The model had 0.79 recall showing that it successfully identified 79% of all actual "Adult" individuals. This shows a relatively high recall, suggesting the model is good at capturing most of the "Adult" instances. The

F1-score for "Adult" is 0.80, which is the harmonic mean of precision and recall. This provides a balanced measure of the model's performance for this class, considering both false positives and false negatives. The support indicates that there are 193 instances of "Adult" individuals in the training dataset.

B. Middle-aged Class

When the model predicted an individual was "Middle-aged," it obtained a precision of 0.77, meaning that it was correct 77% of the time. This is also a good precision which is very close to the one obtained in the "Adult" class. As for recall, the model obtained 0.79 indicating that the model was able to only identify only 79% of all actual "Middle-aged" individuals. This value is significantly lower compared to the other classes, indicating that the model did not struggle to identify "Middle-aged" individuals. The F1-score value for "Middle-aged" is 0.78, which is the lowest value among all classes. This lower F1-score is primarily caused as a result of poor recall value obtained. In the support area, it shows that there are 193 instances of "Middle-aged" individuals in the training dataset.

C. Under-aged Class

When the model predicted an individual was "Underage," it was correct 80% of the time. This gives a precision value of 0.80 which is the highest precision among all classes, indicating strong confidence in its positive predictions for this group. The model also successfully identified 79% of all actual "Underage" individuals. This is the highest recall value obtained (0.79), demonstrating the model's excellent ability to capture instances of "Underage" individuals. The F1-score for "Underage" is 0.79, which indicates that the model performs exceptionally well for the "Underage" class, achieving a good balance between precision and recall. The Support indicates 194 instances of "Underage" individuals in the training dataset.

D. Overall Model Performance

Vision Transformers (ViTs) generally outperform Traditional Artificial Neural Networks (ANNs), including Convolutional Neural Networks (CNNs), in facial detection and recognition tasks due to their self-attention mechanism, which allows them to capture long-range dependencies and global contexts in images more effectively than the local inductive biases of CNNs. While ViTs offer improved accuracy, robustness to occlusions and distance, and efficient inference speed, they often require larger datasets and more computational resources for training compared to traditional ANNs.

The Vision Transformer (ViT) model demonstrated promising performance in predicting underage voters, achieving an overall accuracy of 0.79. This result indicates that approximately 79% of the model's predictions were

correct, reflecting a robust generalization capability across the dataset. Notably, both the macro and weighted average F1-scores were also recorded at 0.79, underscoring the model’s balanced performance across the classification task.

The equivalence of macro average and weighted average scores suggests that the model performs consistently across all classes; underage and eligible voters. The macro average treats each class equally, regardless of its frequency, while the weighted average accounts for class imbalance by assigning weights based on class prevalence. The parity between these scores implies that the dataset was relatively balanced and that the model did not disproportionately favour the majority class. This is particularly important in civic applications, where equitable treatment of all demographic groups is essential to uphold fairness and avoid systemic bias.

Also, a good F1-score reflects a well-maintained balance between precision and recall. In the context of voter eligibility, this balance is critical. High precision ensures that individuals predicted as underage are indeed underage, minimizing the risk of erroneously excluding eligible voters. Conversely, high recall ensures that most actual underage individuals are correctly identified, reducing the likelihood of ineligible participation. The model’s ability to maintain this trade-off suggests that it is well-suited for deployment in sensitive electoral systems where both types of misclassification carry significant implications.

This study generally focuses on classification accuracy as it is the primary measure of model performance in machine learning. The number of correctly predicted classes could be identified through the confusion matrix as provided in Figure 5 which intuitively reflects the prediction results and classification of the model on the test set.

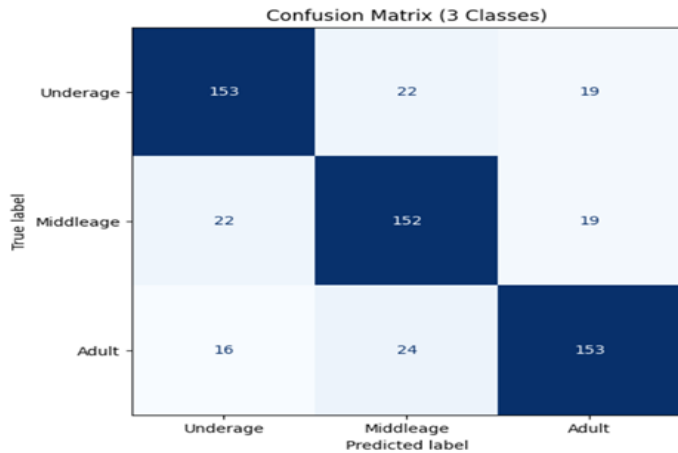


Figure 5: Confusion Matrix

The confusion matrix provides a detailed breakdown of the performance of a loaded model in classifying individuals into three age groups: "Adult", "Middle-aged," and "Underage."

The actual rows represent the true, known categories of individuals. The Predicted columns represent the categories that the model assigned to the individuals. Each cell contains the count (values) of individuals whose actual class is given by the row label and whose predicted class is given by the column label.

The total samples are the sum of all cells (153 + 22 + 19 + 22 + 152 + 19 + 16 + 24 + 153) which is equal to 580 samples. The total correct predictions are the sum of all diagonal values (153 + 152 + 153) which is equal to 458 samples. The overall accuracy is (Total Correct Predictions) / (Total Samples) = 458 / 580 which gives 0.7896 or 79% approximately. This indicates moderately good overall accuracy. The model excels at identifying "Underage" individuals, boasting a very high recall (80%) and strong precision (79%). This means it rarely misses an actual underage person and, when it predicts Underage, it's usually correct.

E. Comparison Of Classification Results With Previous Studies

This section provides a contextual analysis of the performance achieved by the current research in relation to prior work within the domain. This comparison, detailed in the accompanying table, benchmarks key metrics such as Accuracy, Precision, Recall, and F1-Score against established studies by Adeniyi & Adeshina (2019) and Dayo (2022). It serves to highlight evolutionary progress, trade-offs, and relative standing of different methodological approaches from convolutional neural networks and vision transformers to iris-based neural networks in addressing the challenge of age classification for voter eligibility.

Table 2: Comparison of classification results with previous studies

No	Studies	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	Proposed	79	80	79	79
2	(Dayo, 2022)	91.7	-	-	-
3	(Adeniyi & Adeshina, 2019)	77.67	-	-	-

V. CONCLUSION

In Nigeria, due to low digital literacy in INEC elections leads to difficulties using tools like BVAS and IReV, poor access to reliable information, and increased vulnerability to misinformation. These issues are worsened by weak infrastructure, inadequate training, and the digital divide. Despite INEC's tech efforts, limited strategic planning and educator support hinder digital skill development and public trust in electoral processes.

This study illustrates the effectiveness of leveraging deep learning, specifically Vision Transformer architectures, for identifying underage voters via facial analysis. The algorithm, trained on a unique dataset of 2892 photos classified into Underage, Middle-aged, and Adult categories, attained an overall accuracy of 79 percent. It excelled at identifying underage individuals, achieving a precision of 0.80, a recall of 0.79, and an F1 score of 0.79 over 194 occurrences. The Adult group had moderate performance, achieving a precision of 0.80, a recall of 0.79, and an F1 score of 0.80 based on 193 samples. Conversely, the middle age class exhibited the lowest performance, with a precision of 0.77, a recall of 0.79, and an F1 score of 0.78 over 193 samples, signifying the necessity for more sophisticated features. The macro and weighted average F1 scores were 0.79 and 0.79, respectively, indicating consistent although moderate competence across classes. Future research should focus on expanding the dataset to include more diverse and representative samples, improving model accuracy and generalizability. Incorporating multimodal biometrics like iris or fingerprint data can enhance performance, while deploying lightweight models on mobile devices would support real-time use.

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