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Dynamic Horizontal Voting Ensemble Deep Learning Approach to Combined Classification for Human Age, Gender and Ethnicity Soft Biometric Using Fingerprint Pattern

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ABSTRACT

There is paucity of information regarding the probability that fingerprints may reveal combined soft biometric trait of human age, gender, and ethnicity. This challenge is due to lack of data. This has however, prompted academics to conduct their demographic classification-related work using the limited fingerprint dataset that is now available. However, complete fingerprint datasets collected under conventional and real-world conditions are not easily available for research reasons. This research aims to design a multi-task Deep Learning model for classifying the combined traits of ethnicity, gender, and age group estimation using fingerprint pattern. The fingerprint database was collected using a live scan method in real-world conditions, with subjects from three most numerous racial groups of Nigeria which are Yoruba, Igbo and Hausa, with consideration of the subject gender and age groups. The proposed method for the fingerprint image classification and training is the novel Dynamic Horizontal Voting Ensemble (DHVE) with Hybrid of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) being utilized as the base (weak) learner. The dynamic selection method was utilized to determine classifiers in the normal horizontal voting ensemble, hence enhancing the ensemble technique's average accuracy. Standard performance classification metric inclusive of Accuracy, hold in thoughts, Precision, and F1 rating had been implemented to evaluate the model's performance. The result shows 76% accuracy in predicting person's combined age group, ethnicity and gender. We also compared its performance against other approaches. It outperforms other cutting-edge algorithm like the CNN model in terms of performance metrics.

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1. Introduction

Humans have numerous demographic characteristics, such as ethnicity, gender, and age, that enable them to naturally recognize themselves [1]. These demographic characteristics are soft biometrics that provide supplementary information about a person. The drive to find methods for automatically classifying these supplementary data has created remarkable new research opportunities and challenges. Today, biometric systems are utilized to address some of these issues. According to [2], the field of biometrics focuses on identifying individuals by their bodily, psychological, and behavioral characteristics, which include fingerprint, face and iris. Fingerprints are the most commonly employed biometric defining trait [3]. According to the study by [2], discovered that additional information, including age, weight, ethnicity, can be inferred from the fingerprint pattern. Due to their lack of uniqueness, soft biometrics are insufficient to identify persons, but they can enhance the efficiency of the primary biometric system [2].

Compared to certain other modalities, there is a dearth of exhaustive research on the feasibility of fingerprint-based information regarding the combined characteristics of race, gender, and age. This is due to data scarcity, which has obliged academics to conduct their demographic classification-related work on the restricted fingerprint dataset that is now available. The majority of these fingerprint datasets are collected under controlled conditions or using the obsolete ink-and-paper method. In contrast, extensive fingerprint datasets collected under conventional and real-world situations are not widely available for scientific purposes. The reason behind this work, which seeks to develop an extensive and accurate databases of fingerprints utilizing live-scan technology which takes into consideration ethnicity of the subject, gender, and age. Similar dataset collected by [4] and [5] focused on ethnicity and gender, the age factor was not covered. It is anticipated that the dataset in this study will resolve the issues mentioned in this assertion. The proposed method is going to be developed using a deep learning model. The remainder of this research is as follows: section II addresses relevant works, section III examines methodology while section IV shows the result and afterward, conclusion with proposed future works in section V.

2. Related Works

A person's ethnicity, age and gender may be ascertained, according to recent studies using biometric data [6-9]. Face and iris modalities have been widely investigated. [10] suggested that the tremendous progress made so far in the automatic prediction of demographics on facial and iris characteristics was due to the availability of sufficient and quality dataset. Numerous face-based gender, age group, and categorization based on race approaches have been created, such as universal face analysis, feature extraction, 3D model method, and periocular features fusion. [10].

In recent studies by [11][12][13], numerous soft biometric features were used to classify full human demographic traits of gender and age group which includes hand, voice records, and fingerprint as soft biometric characteristics. The results indicate that fingerprints are the best predictor of age. The repetition rate of the loop, arch, and other patterns varies across a range of ethnic groups, according to earlier studies on fingerprint features. [14]. Although many biometric literatures have produced commendable classifications on various biometrics, a thorough review of existing literatures revealed that, to the extent that we know, no research has been conducted on the possibility of combining ethnicity, gender and age classification using fingerprint pattern. Available efforts have focused primarily on facial features [15][16]. Recent research by [17][18] on fingerprint-based focused on two traits. This study aims to close this gap by providing an extensive fingerprint dataset via live scan, classifying the combined soft biometric features (ethnicity, gender, and age group) and comparing proposed model with existing models.

3. Methodology

In the proposed Dynamic Horizontal Voting Ensemble (DHVE), intermediate modeling results are saved with a predetermined local accuracy threshold as selection criteria. The output of the models is combined using voting techniques to increase prediction accuracy. At prediction point, the best of single sub-classifier score or the ensemble score is dynamically considered for the final prediction. Since we intend to achieve our objective through a dynamic scheme, hence we refer to our method as a dynamic horizontal voting ensemble. The proposed model framework consists of four phases, as presented in Figure 1. The initial step consists of data gathering and preprocessing, followed by model construction and training, the dynamic ensemble phase, and the dynamic classifier phase.

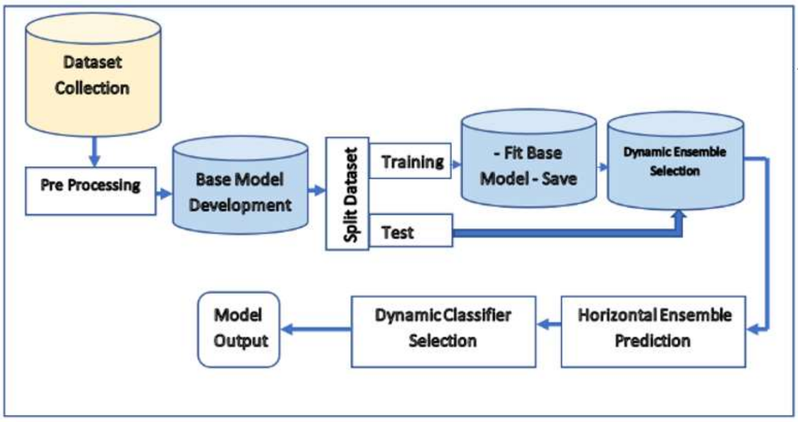

Figure 1 Proposed DHVE Model Framework

3.1. Data Gathering

This work acquires 450 subject fingerprint images. Ten (10) of each subject's fingerprints were collected, given a 4,500 images sample altogether. The diverse subjects represent three predominant Nigerian ethnic groupings (Hausa, Igbo, and Yoruba), as well as distinct gender and age categories. This study considers the following age groups: ages less than 12 as children, ages 12 to 19 as teens, ages 20 to 50 as adults, and above 50 as seniors. As stated in Table 1, fingerprint images are grouped for the purposes of this experiment into possible classes. Totaling twenty-four (24) classes. Table 1 illustrates the frequency for each class distribution in the investigation.

Table 1 The Dataset Possible Combinations

Biometric Class Combination	Training Set	Test Set	Total
Male, Hausa, Child (MHC)	208	52	260
Male, Hausa, Teen (MHT)	176	44	220
Male, Hausa, Adult (MHA)	184	46	230
Male, Hausa, Senior (MHS)	200	50	250
Male, Igbo, Child (MIC)	88	22	110
Male, Igbo, Teen (MIT)	136	34	170
Male, Igbo, Adult (MIA)	168	42	210

Biometric Class Combination	Training Set	Test Set	Total
Male, Igbo, Senior (MIS)	88	22	110
Male, Yoruba, Child (MYC)	216	54	270
Male, Yoruba, Teen (MYT)	160	40	200
Male, Yoruba, Adult (MYA)	200	50	250
Male, Yoruba, Senior (MYS)	152	38	190
Female, Hausa, Child (FHC)	136	34	170
Female, Hausa, Teen (FHT)	168	42	210
Female, Hausa, Adult (FHA)	152	38	190
Female, Hausa, Senior (FHS)	72	18	90
Female, Igbo, Child (FIC)	136	34	170
Female, Igbo, Teen (FIT)	200	50	250
Female, Igbo, Adult (FIA)	168	42	210
Female, Igbo, Senior (FIS)	120	30	150
Female, Yoruba, Child (FYC)	152	38	190
Female, Yoruba, Teen (FYT)	112	28	140
Female, Yoruba, Adult (FYA)	160	40	200
Female, Yoruba, Senior (FYS)	48	12	60
Total	**3,600**	**900**	**4,500**

Images are 8-bit gray-level with extension bmp files. Resolution is 357 × 392 pixels. Figure 2 show some sample of captured fingerprints images.

(a) Sample Fingerprints from Yoruba Subject

(b) Sample Fingerprints from Hausa Subject

(c) Sample Fingerprints from Igbo Subject

Figure 2 Sample Fingerprints from The Ethnic Groups

3.2. Data Preprocessing Stage

The objective of preprocessing is to reduce noise and eliminate undesirable features [19]. Using a full range of grey levels distributed evenly over the image's histogram, in this study, the histogram of the image was transformed into a uniform histogram using the histogram equalization approach. [20].

Given image t represented as a mat_r by mat_c, where mat_r and mat_c are the row and column dimension of an integer-pixel matrix with intensities varying from 0 to K − 1. K is the total number of potential intensity levels, which is typically 256. Assume p symbolize the normalized histogram of t for each likelihood intensity. So,

$$pn = \frac{\text{number of pixels with intensity } n}{total\ number\ of\ pixel!}$$

n = 0, 1,… K-1.

The required histogram equalized image g is going to be

$$g_{i,j} = \text{floor}((K - 1)\sum_{n=0}^{f_{ij}} p_n), \qquad (1)$$

where floor() round to the closest integer, round numbers.

Equation (1) fully described the histogram equalization of a given image. An edge-preserving bilateral-filter was employed in the process of denoising and smoothening the image. Bilateral filter, which is an enhancement over Gaussian filter. The formula for Gaussian blurring is stated in Equation (2) below:

$$GB[I]_p = \sum_{q \in S} G_\sigma(\| p - q \|)\ I_q \tag{2}$$

where $G\sigma((\| p - q \|))$ is the 2D kernel Gaussian function. By means of a declining weight sequence in response to such spatial separation based on middle point p, Gaussian filtering computes the image pixels weighted average of nearby places. The Gaussian G(||p q||) provides the pixel q, where a neighborhood-size defining factor is σ. Comparable to how Gaussian convolution is expressed, The weighted average of nearby pixels is what the bilateral filter does. On the other hand, the bilateral filter smoothes while maintaining edges by taking into account the value disparity between adjacent pixels. Given BF[I], where Iq, Ip represents image pixel and midpoint respectively, which defines the bilateral filter for the image I.

$$BF[I]_p = \frac{1}{W_P} \sum_{q \in S} G_{\sigma_s}(\| p - q)\ G_{\sigma_r}(I_p - I_q)\ I_q \tag{3}$$

Wp functions as a parameter for normalization to make sure that pixel weights add up to 1.

$$W_p = \sum_{q \in S} G_{\sigma_s}(\| p - q)\ G_{\sigma_r}(I_p - I_q)\ I_q \tag{4}$$

In Equation (4), the factors σs and σr specify the image I level of filtration as shown in Equation (3) above.

3.3. Training Base Model Options

The CNN-LSTM architecture utilized for the base learner model is depicted in Figure 3. Utilizing the CNN model, features were extracted from the input data. Six layers total—two convolutional, two maxpooling, and two fully connected—make up this structure. It is a multi-class classification problem that is being considered. The CNN model receives fingerprint images in the format of 96x96 pixels normalized to [0, 1]. The CNN output is reshaped into (batch-size, Height, Width*channel) and providing a 3D dataset for the LSTM layer to take in is the strategy used in this experiment to ensure handshaking between the two layers. H and W stand for the feature map's height and breadth in the reshape parameters. The approach, for example, is to utilize the Flatten layer after the CNN and before the LSTM to project the output to a 1-dimensional sequence using Lambda function to activate the reshape sub-routine since the Conv2D accepts 2-dimensional input or output while an LSTM accepts 1-dimensional input. The base model's training options are as follows: using a mini-batch size of 128 and a validation split of 0.2, 150 tuning epochs were applied to the model during training. Monitoring the performance of the model by using early stopping strategy. During the optimization process, the Adam algorithm was applied with a 0.001 learning rate and category cross entropy as the loss function. The two LSTM layers that were implemented were each designed with 16 and 96 units. With a Softmax activation, the LSTM layer output is sent into the fully connected (FC) output layer. Combining the Softmax with cross-entropy loss yields a discrete probability distribution vector that is beneficial. The Softmax layer, which determines the confidence probability of the output fingerprints, is connected to the FC layer.

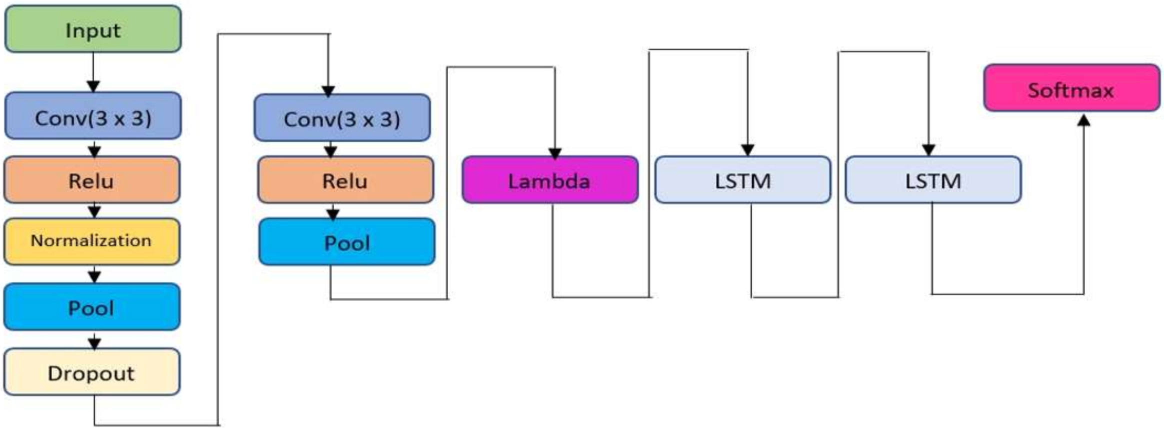

Figure 3 Architecture of CNN-LSTM

3.4 Dynamic Selection Scheme for Horizontal Voting Ensemble

The proposed dynamic ensemble selection approach for the horizontal voting ensemble is detailed in Algorithm A. By dynamically selecting competent models on the basis of the validation accuracy measure via base learning on the training set, the approach creates a horizontal voting ensemble for classification. If the model accuracy is equal to or greater than the set threshold, such training epoch is saved. In order to create a prediction ensemble, the best combination of the saved models is selected as well based on the necessary ensemble size. In contrast to the existing method, in which ensemble members are deliberately selected, dynamic selection permits the most effective models to participate in the ensemble during prediction. The procedure is enumerated in Algorithm A.

Algorithm A: Dynamic stage
Input
Dataset: $Data_{set} = Data_{Trn} \cup Data_{Test}$
Component $\mathrm{Data_{set}}$ Intersection in $Data_{Trn}$ & $Data_{Test} = \emptyset$
Set initial values for J,j and $\mathrm{K_{set}}$
Set list $\mathrm{En_{j=}}$ [ ]
Set selection *threshold_value*
Procedure
While i ≤ J **do**
  Train $Data_{Trn}$ for one epoch
    if $\mathrm{epoch}_{Acc} \geq$ *threshold_value*:
     epoch.save(list(i))
     increment i by 1
  end while
Assign all_epoch saved to K_{set}
Arrange K_{set} in ascending order of epoch_{Acc}
Assign $\mathrm{K_{set}}$ to $\mathrm{En_j}$ where j is the first $\mathrm{j^{th}}$ elements of $\mathrm{K_{set}}$
Output: $En_{j,}j$

The next Algorithm B explains how to dynamically select the final classifier for prediction. The first algorithm output was given as input to the next algorithm. This study employs 150 epochs and an ensemble range of 1 to 50.

Algorithm B: Final Phase for DHVE Model

Input:

Build ensemble of varying size of $En_j = \{e_1,..e_j\}$

Evaluate varying size of ensemble En_j on $Data_{test} = \{Data_{t1},..,Data_{tj}\}$

Set ensemble result Ens_{result},

Set initial value for list variables Predicts, $Model_{result}$ = [ ]

Set parameters: $Model_{max\text{-}score}$, Sub_{set}, Sngle_result

Procedure:

While i ≤ j **do:**

$Sub_{set} = En_j$ [:i]

for all epoch in range i:

Train $Data_{test}$ in Sub_{set}(epoch), assign output to predicti

predicti = predicti + Predicts

epoch = epoch + 1

end for

$$P = \sum_{\text{predicti}}^{\text{predicti} \in \text{Predicts}} \text{predicti}$$

Ens_{result} = argmax(P)

for all j in range (1, i+1):

Sngle_result = E*n*[j-1]. P($Data_{test}$)

Append Sngle_result *to* $Model_{result}$

end for

epoch = 1

end while

Assign highest score in list $Model_{result}$ to $Model_{max\_score}$

Set final Ens_{result} value to most competent of $Model_{max\_score}$ and initial Ens_{result} score

Output: Ens_{result}

At two crucial points in the model's evolution, the dynamic approach was implemented. First, when picking ensemble members, and second, when a single classifier's output outperforms the ensemble forecast.

4. Results and Discussions

Table 2 displays the DHVE output accuracy, precision, recall, and F1 score following training. Parameters that affect performance measurement of the algorithm includes the quality of the image and the methods used for evaluation.

Table 2 DHVE Model's Classification Performance on Combined Classes

Fingerprints	Precision	Recall	F1-score	Support
Male, Hausa, Child	0.97	0.98	1.00	52
Male, Hausa, Teen	0.33	0.36	0.35	44
Male, Hausa, Adult	0.45	0.43	0.44	46
Male, Hausa, Senior	0.49	0.50	0.50	50
Male, Igbo, Child	0.61	0.64	0.62	22
Male, Igbo, Teen	0.43	0.53	0.47	34
Male, Igbo, Adult	0.32	0.45	0.38	42
Male, Igbo, Senior	0.36	0.23	0.28	22
Male, Yoruba, Child	0.51	0.48	0.50	54
Male, Yoruba, Teen	0.74	0.72	0.73	40
Male, Yoruba, Adult	0.58	0.62	0.60	50
Male, Yoruba, Senior	0.78	0.74	0.76	38
Female, Hausa, Child	0.45	0.41	0.43	34

Fingerprints	Precision	Recall	F1-score	Support
Female, Hausa, Teen	0.20	0.21	0.21	42
Female, Hausa, Adult	0.42	0.39	0.41	38
Female, Hausa, Senior	1.00	0.98	0.98	18
Female, Igbo, Child	0.52	0.44	0.48	34
Female, Igbo, Teen	0.94	1.00	0.97	50
Female, Igbo, Adult	0.73	0.45	0.56	42
Female, Igbo, Senior	0.20	0.20	0.20	30
Female, Yoruba, Child	0.39	0.34	0.37	38
Female, Yoruba, Teen	0.48	0.75	0.58	28
Female, Yoruba, Adult	0.52	0.42	0.47	40
Female, Yoruba, Senior	0.67	0.50	0.57	12

According to Table 2, the classification results for the classes (Female, Hausa, Senior), (Female, Igbo, Teen), and (Male, Hausa, Child) is same in terms of Precision, Recall, and F1-score which equal 1. This suggests that every positive sample is categorized as positive, whereas for Precision levels of 1, negative samples are marked as negative. A recall score of 1 indicates that all genuine Positives were correctly detected. For value of F1 score equal 1 indicates the algorithm classified unbalanced data flawlessly. The model's accuracy score is 76%, indicated in Table 3, while Figure 5 depicts the Confusion Matrix.

Table 3 General Model Classifications Performance for DHVE

Classification Parameter	Precision	Recall	F1-score	Support
Accuracy			0.76	900
Macro avg	0.76	0.76	0.76	900
Weighted avg	0.77	0.76	0.76	900

Table 3 shows the macro and weighted averages for precision, recall and F1 score are respectively 0.76, 0.76 and 0.76. This demonstrates the proposed model has a descent classification efficiency for each performance indicator. The macro and weighted average F1 score of 0.76 indicates that the proposed model classified imbalance data well. Figure 4 shows the Avg ROC-AUC

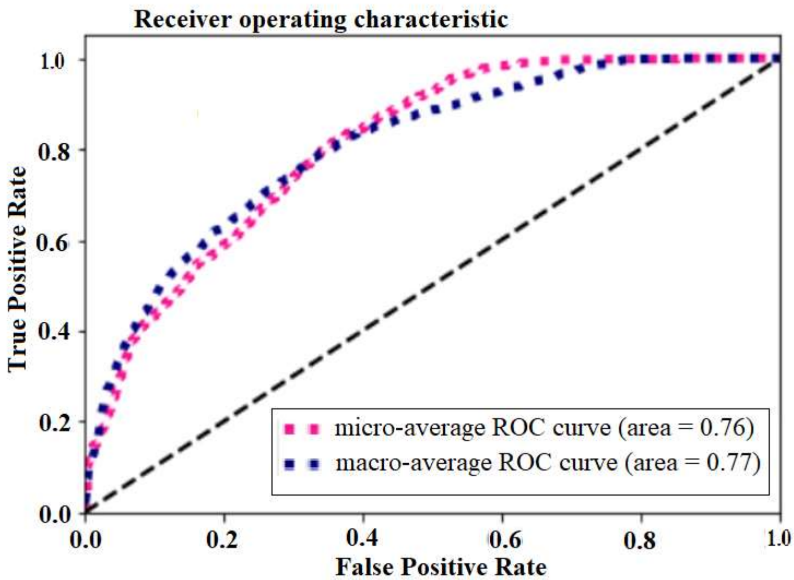

Figure 4 Average ROC-AUC Plot

The DHVE Mixed Classification Model's Average Receiver Operator Characteristics (ROC) Curve is depicted in Figure 4. It displays the Probability - based Plotting the TPR versus the FPR at different levels and effectively separating noise. The Area Under the Curve (AUC) estimates the classifier's capability in differentiating between each class. The greater the values, the more accurately the classifier can differentiate between positive and negative classifications. The ROC curve compares the rate of true positives to the rate of false positives and indicates how well a model can categorize. Figure 4 depicts the micro and macro averages for all classes that are being tested. The model makes a distinction across positive and negative categories with outstanding accuracy, per class averages close to 1.00, inferred from the average curve (through all classes). The Confusion matrix for the DHVE classification is depicted in Figure 5.

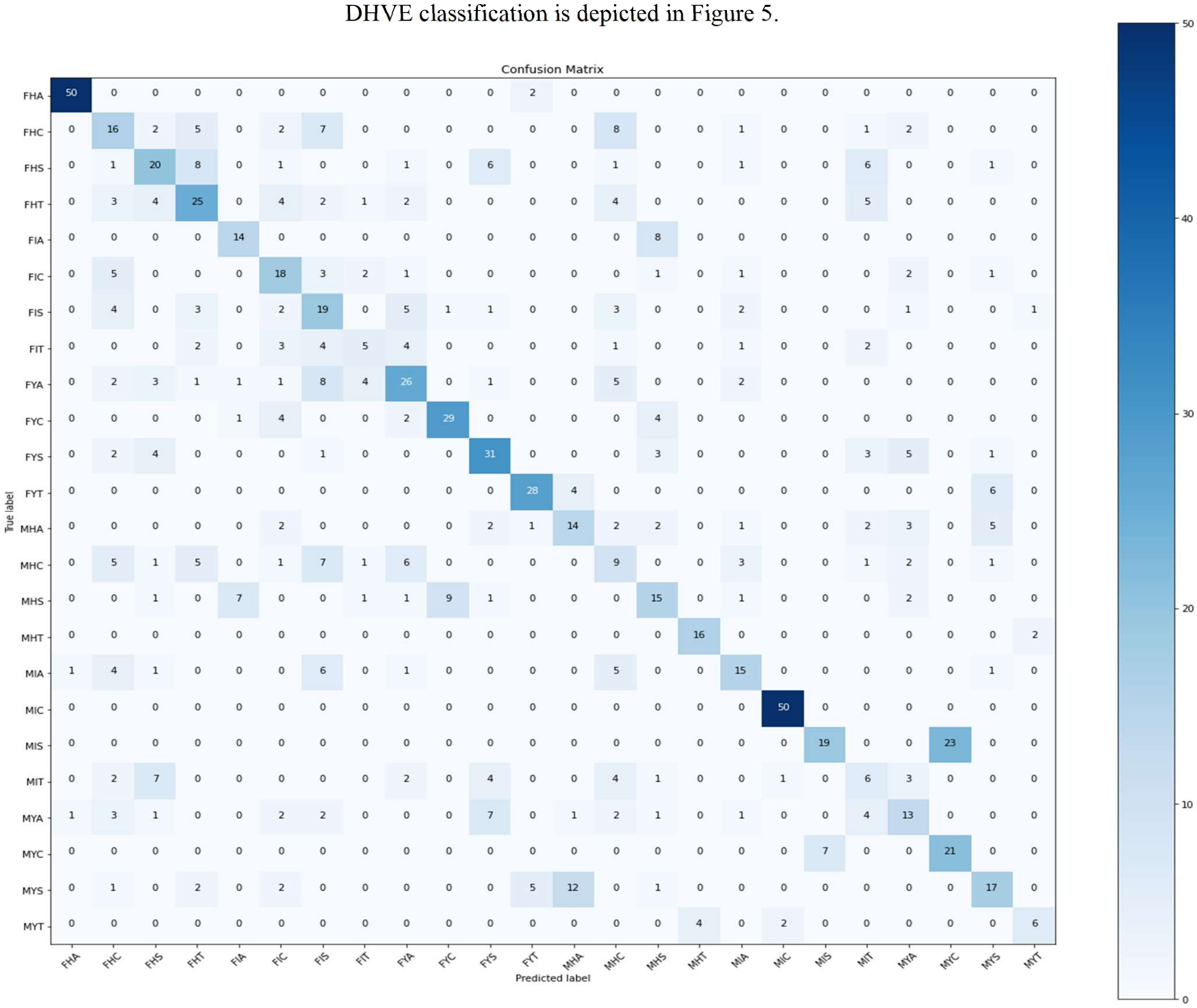

Figure 5 Confusion Matrix for Combined Classification

Actual values for each group are provided in Table 1. Both the actual and anticipated values for the categories (Female, Hausa, Adult) and (Male, Igbo, Child) were correctly classified, as shown by the Confusion matrix for the various classes. The classification accuracy of other pairings, such as (Female, Hausa, Adult), (Female, Yoruba, Child), and (Female, Yoruba, Teen), is remarkable. There are combinations such as (Male, Yoruba, Teen), (Male, Hausa, Child), and (Female, Igbo, Teen) that demonstrate poor classification performance, which is mostly due to lack of sufficient training data. Figure 6 shows the performance comparison of DHVE model with CNN-LSTM and HVE.

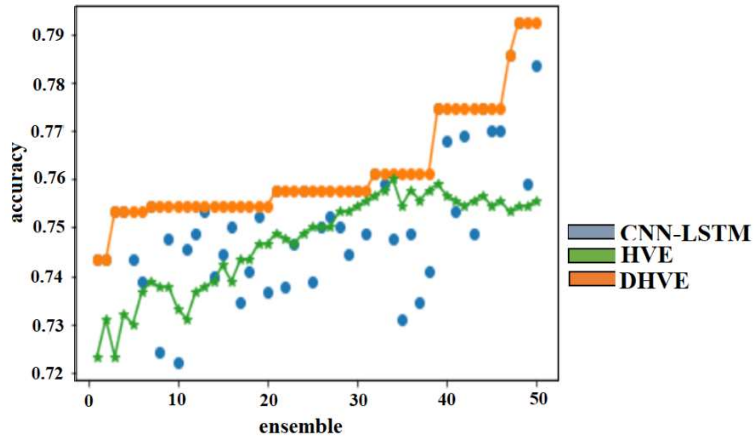

Figure 6 Plot Comparing DHVE's Performance with Other Models

The blue dots on the line plot in Figure 6 represent CNN-LSTM, the green points represent HVE, and the orange points represent DHVE. The accuracy of the CNN-LSTM, HVE, and DHVE models are respectively 0.752, 0.747, and 0.762. The plot for the proposed DHVE demonstrates that the model's performance improves as the ensemble size increases after 20, 30, 40, and somewhere around 47. The flattening of the curve compared to the scatterplot of a single model demonstrates the stability of the proposed model. DHVE significantly achieves more accuracy than all other models with a total precision of 0.762%. Table 4 shows the performance metric of the models.

Table 4 Performance Comparison on Precision, Recall, F1 and Accuracy

Models	Precision	Recall	F1 Score	Accuracy (%)
CNN-LSTM	75.0	75.0	76.0	75.0
HVE	73.0	74.0	74.0	74.0
DHVE	76.0	76.0	76.0	76.0

Table 4 compares the classification precision, recall, F1 score, and accuracy of the CNN-LSTM and HVE models with the proposed DHVE model. The fact that the DHVE model's Precision, Recall, F1 score, and Accuracy score are all equal to 76.0 demonstrates that the introduction of a dynamic scheme into horizontal voting ensemble enhances the accuracy of the final prediction.

A model for detecting a combination of gender, age estimation, and ethnic group using fingerprint data has been developed based on the findings of this study. In addition, this study has demonstrated experimentally that the adoption of a dynamic scheme has improved the performance of the horizontal voting ensemble algorithm. In the experiment, the DHVE model fared better than all other models. in terms of classification metrics. The level of accuracy reached in this experiment was due to lack of sufficient training data for most of the classes. With more dataset, the model's performance accuracy can be improved.

We compared the effectiveness of the suggested method with two cutting-edge dynamic selection approaches that have been well-established in the literatures. The comparison was based on same dataset used in this study. KNORA algorithm is dynamic classifier selection based algorithm which uses the oracle idea and was proposed by [21]. Dynamic Selection On Complexity (DSOC) algorithm which utilizes characteristics relevant to the features complexity when evaluating the classifier [22]. The performance across all DS approaches is extremely dependent on the establishment of a local region. In fact, a number of recent articles have noted that by focusing on properly identifying these areas, it is feasible to enhance the outcomes of DS (Dynamic Selection) approaches. Typically, the K-NN approach is used to determine the local areas. It is crucial to select the k value to a value that's appropriate for the dataset to be used because it determines the neighborhood's size. Significant values in the training set could be removed from the neighborhood if k is too small, while too large value for k may result in the relevant samples being masked by too many examples. In this research, ten (10) different values of k from 2 to 12 are being explored to determine the best outcome on the dataset. Figure 7 and Figure 8 demonstrates the accuracy variation of DSOC and KNORA-U models respectively on the combined trait dataset used in this study with k numbers ranging from 2 to 12. Table 5 shows the performance comparative analysis of the algorithms.

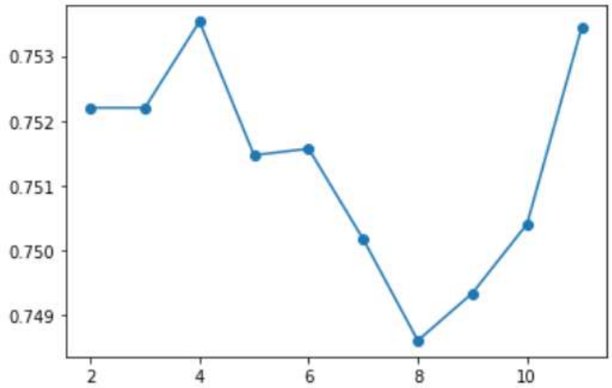

Figure 7 Plot Showing DSOC with Optimum Accuracy of 0.754% at Neighborhood Size of k = 4

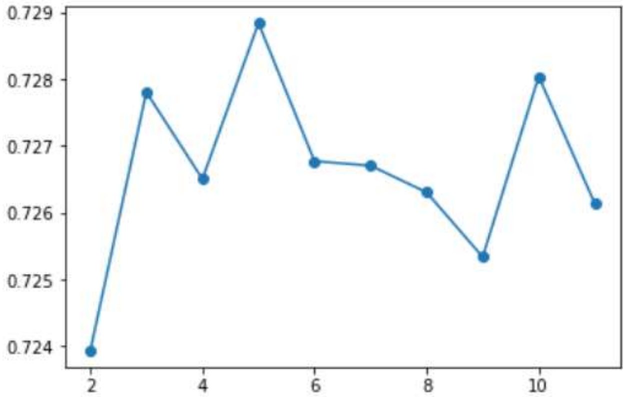

Figure 8 Line Plot for KNORA with Optimum Accuracy of 0.729% at Neighborhood Size of k = 5

Table 5 Comparing Models Performance

Dataset	Model Accuracy (%)		
	DSOC	KNORA-U	DHVE
Combined Trait	75	72	76

5. Conclusions

The study's findings point to DHVE Model as a suitable tool for the fingerprint recognition in biometric system. The performance of the model indicates that fingerprints could be classified with little error according to Gender, Age, and Ethnicity. The classification performance of the model can be enhanced by training with larger dataset. Future research could also explore the use of adaptive preprocessing techniques to augment low-quality fingerprint images in order to increase the classification accuracy of models.

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