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Deep Learning Ensemble Approach to Age Group Classification Based On Fingerprint Pattern

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Abstract

The age distribution of a population is extremely valuable to any business or country. In order to make decisions with regard to facility allocations and other social economic developmental issues, determination of age group distribution information is essential. The attempt to deceive others about one's age is a significant problem in the sporting world, as well as in other organizations and electoral processes. Therefore, there is a requirement for an age detection system, which is required to authenticate individual claims. Fingerprint-based age estimate research is scarce due to paucity of dataset. However, there are indications that fingerprints can reveal age demographic. This study's objective is to live-scan fingerprint images in order to identify age groups. This study proposed novel Dynamic Horizontal Voting Ensemble (DHVE) with Hybrid of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) as the base learner. The method constructs a horizontal voting ensemble for prediction by dynamically determining proficient models based on the validation accuracy metric during base learner training on the training set. Accuracy, recall, precision, and the F1 score were employed as standard performance metrics to measures the model's performance analysis. According to this study, predicting individual age group was accurate to a degree of above 91%. The DHVE network performed well due to the design of the layers. Integration of dynamic selection approach to horizontal voting ensemble improved the average performance of the model output.

Keywords: *Deep learning, ensemble, age group, demographic, fingerprint, performance metric.*

1. Introduction

Very important information to every organization or a nation is the age bracket distribution. It is key in taking necessary decisions concerning facility distributions, restricted access and developmental issues. Falsification of age is a big challenge in sport, organizations and during elections. Hence, the need for an age detector system which is necessary to ensure the integrity of information available [1]. Prevalent methods for age estimation involve the use of physical features such as face, teeth, bones and other parts that support conventional methods [2]. Only few researches have been conducted in the estimation of age using the fingerprint. However, evidences abound that age bracket can be determined through individual fingerprint Fingerprints are one of those strange twists and wonders of nature. It is termed human built-in identity cards [3]. Fingerprints are considered as the oldest and most widely used in the world for biometric identification [4]. It is further described by [5] as the most extensively deployed recognition system due to its high accuracy and public acceptability compare with other biometric traits. It is the pattern of ridges and valleys on the surface of a fingertip [5], and no two individual has same fingerprint and it is unique to every man [6,7]. However, it has been found that having an efficient age group identification system is a key facilitator for achieving a number of key age group development results, including the elimination of age falsification in electioneering processes, sports, and other areas where age plays a role in the development.

Out of the several methods involved in verify human identity, biometric system offers a better approach due to it numerous advantageous features over other methods [8]. Biometrics is defined as the science of personal identification centered on their physical, behavioral, and physiological traits such as fingerprint, face, iris, gait and voice [9]. It is the science of using human body for identification purposes. Biometric can be sub-divided into hard and soft biometrics [8]. Primary or hard biometric deals with physical and behavioral traits such as hand geometry, voice, fingerprint, face, iris, Deoxyribonucleic acid (DNA), gait, palm print and keystroke dynamics [10]. Soft biometrics deals with secondary characteristics that provide other information that are not adequate to identify a person clearly such as age, gender, ethnicity, skin color, scars, and height [8]. They are soft because they are not sufficient enough to uniquely identify individual [9].

An exhaustive research study conducted by forensic scientists has resulted in the discovery of a unique pattern that is embedded in the fingerprint. The researchers came to the conclusion that a close examination of the minutia of the fingerprint can provide an insight to a person's age group as well as other vital information with regard to an individual [11]. These distinctive characteristics of fingerprints can be utilized to determine

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an individual's age based on comparison to other people's prints.

Classifying human age groups based on fingerprint patterns has been the subject of several research, each of which has shown promising results. A method applying discrete wavelet transform (DWT) and the singular value decomposition (SVD) feature extractors to a person fingerprint image in other to estimate the age was proposed [12]. KNN was used as the classifier. The dataset used was collected using scanner with every image of size 260x300 pixels with resolution of 500 at 256 grey levels. All the ten fingers were captured making a total of 3570 fingerprints of which 1590 were female and 1980 were male fingerprints. 2/3 of the total images were used for the training and the remaining for classification. Fingerprints classification were grouped into five classes: up to 12, 13-19, 20-25, 26-35 and 36 and above. The performance of the system shows accuracy of 96.67%, 71.75%, 86.26%, 76.39% and 53.14% in the five groups for male and by 66.67%, 63.64%, 76.77%, 72.41% and 16.79% for female.

In a study, 500 fingerprints were captured from 10 finger of fifty Turkish individuals with the sole aim of estimating their age bracket from fingerprints [13]. The fingerprints obtained were transformed from features to binary images of 1x153600 matrix. KNN classification algorithm was used to classify based on distance measurement by means of "Euclidian distance" classifier. Performance rate of 93.3% for male and 83.0% for female within the age bracket 18- 24. A model to enhance fingerprint image quality to improve performance accuracy particularly in the elderly was designed [14]. Image enhancement was done by applying Local Binary Pattern (LBP) and the Local Phase Quantization (LPQ) operators. The model was evaluated using fingerprint images captured from 500 subjects. The method achieved success rate of 89.1% for age prediction.

In an investigation, the possibility of using human digital fingerprints to estimate human age-groups [15]. The motivation for the study was based on the fact that the variation in width of human digital fingerprint is limited to certain age group while the fingerprint pattern remains the same through life time. In the proposed method, discriminating features of the fingerprint were extracted using Curvelet Transform, with age estimation under consideration grouped into three (i.e. 6-10, 10-14 and 14-18). The approach uses the extracted features for training and testing classifications using Curvelet coefficients. The high dimensionality in the extracted features were removed by projecting them into principal component (PCA) subspace. K-nearest neighbor (KNN) was used as classifier. The experimental results show the little finger gives the best performance for all the classes under consideration. Age bracket 6-10 shows the best accuracy when only the thumb finger is used for training and testing.

In research conducted in an attempt to checkmate the problem of underage voting during election in Nigeria developed a system that predict human age estimation and gender using fingerprint analysis [1]. 280 fingerprints of various age group and gender were captured using life scan election. Discrete wavelet transform (DWT) + Principal Components Analysis (PCA) was used for age classification, while Back Propagation Neural Network was used for gender classification. 140 of the fingerprints were used for learning of which 70 were males and 70 females respectively. The age bracket was grouped thus; 1-10, 11-20, 21- 30, 31-40, 41-50, 51-60 and 61-70 accordingly. The discriminating feature used for gender classification is the Ridge Thickness Valley Thickness Ratio (RTVTR). Experiment Result shows accuracy of 82.14% for age estimation classification.

In research on a multi-resolution texture technique for automatic age-group estimation using digital fingerprints with reference point generation for poor quality images [16]. This study was motivated by the varying texture of human digital fingerprint as the person ages though the fingerprint pattern remains the same. 360 fingerprints images were captured from 36 subjects using live scan of which 18 were males and the other 18 females. The fingerprints obtained were distributed proportionally among the various gender to avoid distribution bias. The age bracket under consideration are 6-10, 10-14 and 14-18. 250 fingerprints were used for learning process and 100 for testing. The proposed novel approach Extracted features at different resolutions using Gabor filters and Wavelet based noise removal was applied to reduce the feature loss. Three other state-of-the-art classifiers were used to adjudge the performance accuracy of the proposed model. The results from the experiment shows the possibility of age-groups identification from digital fingerprint, particularly children. Classification accuracy of 80% for age group below 14 was achieved.

In a recent research, a comprehensive human demographic attributes of gender and age group were classified from multiple soft biometric traits [17]. Soft biometric traits considered in the research are hand, voice recordings and fingerprint. For the purpose of the research, hand videos, fingerprints and voice were obtained from 560 African subjects. The subject distribution consists of 197 females and 363 males. Right index finger of each of the subject were captured in two sessions. The images are in gray scale of 640x480 pixels. Convolutional neural networks (CNN) was used to train classifiers for fingerprint, voice and hand. The results show that age is best predicted from fingerprint.

To sum up, the bulk of the previous articles used ridge features for classification, while some used the ink method for fingerprint collection. One of the difficulties of this approach is that it is impossible to eliminate human error from the data collecting process. Like this, a lack of data makes it difficult to generalize the findings, which is a major limitation. Also, the deep learning technique, which can automatically recognize and define the underlying differences in data that are hard to measure, was not explored by the vast majority of the studies [18,19]. This is what inspired us to conduct this research, which employs a live-scan technology that accounts for the subject's age in order to create a comprehensive and realistic fingerprint dataset. Hopefully, the missing data in this introduction will be filled up by the dataset. An innovative deep learning model, the Dynamic Horizontal Voting Ensemble (DHVE), will be used to implement the proposed system.

2. The Proposed Method

Since fingerprint-based age group categorization is a complicated process, a powerful machine learning strategy needs to be developed for it. Details on the design process and model evaluation are provided here. The proposed Dynamic Horizontal Voting Ensemble (DHVE) system is shown in **Figure 1**. The implementation consists of four stages: stage one being the collecting and preparation of data. Stage two, development and training of the Model. The last stages are a dynamic ensemble selection followed by a prediction phase.

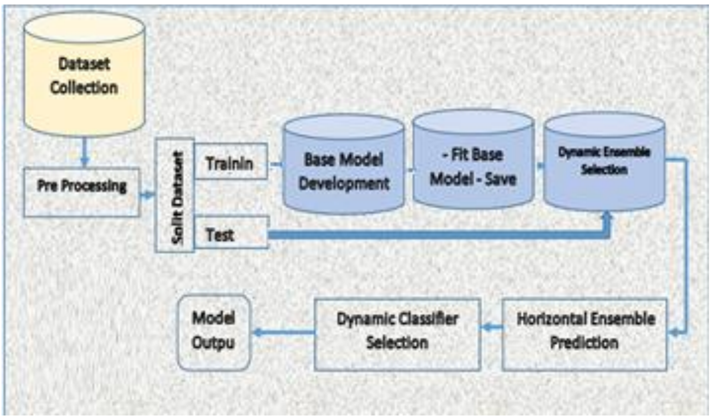

Figure 1. *Dynamic Horizontal Voting Ensemble Framework*

In this study, scanned fingerprint images were captured from a total of 453 Nigerian subjects. However, images from 450 Nigerian subjects were used in this study. Fingerprints from three (3) of the participants were left out due to poor quality. The ten (10) fingerprint of each subjects were captured making a total sample 4500 images 1170, 1190, 1290 and 850 belong to Child, Teen, Adult and Senior age groups respectively. To provide for dataset balance and fairness, only 850 subset images from Child, Teen, Adult and Senior subjects were utilized in this study (See **Table 1**).

Table 1. *Dataset distribution according to age group*

Biometric Class	Training Set	Test Set	Total
Child	680	170	850
Teen	680	170	850
Adult	680	170	850
Senior	680	170	850
Total	2,720	680	3,400

The fingerprint images were labeled with such attributes as image ID, gender, age group, ethnicity and finger type labels (i.e. the thumb, index, middle, ring and little finger labels) as shown in **Figure 2**. The age group categorization are Child (1-12), Teen (13-20), Adult (21-50) and Senior (above 50).

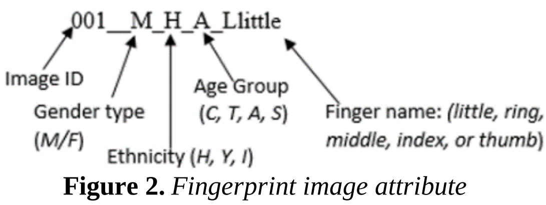

Figure 2. *Fingerprint image attribute*

2.3. Data Preprocessing Stage

The elimination of unwanted features and the minimization of noise are the primary goals of preprocessing [19]. In this study, the histogram equalization approach was utilized [20], which is a method that changes the histogram of an image into a uniform histogram by selecting all of the grey levels uniformly across the histogram of the image. Let f represent an image of dimensions mr by mc, where mr and mc are the rows and columns of a matrix containing integer pixels with intensities from 0 to L 1. Where L is the range of intensities that can be used (often 256). For convenience, we'll refer to p as the normalized histogram of f, where each intensity level is represented by a separate bin. So;

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

n = 0, 1...L-1

The histogram-equalized image g will be described by

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

where floor() round numbers down to the nearest integer. A bilateral filter smoothed and denoised the image while retaining edges. Bilateral filter improves Gaussian filter. Gaussian blurring formula:

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

where Gσ((‖ $p - q$ ‖)) is the 2D kernel Gaussian function. Gaussian filtering computes the image pixels weighted average of nearby spots with a declining weight pattern with respect to spatial distance from the midpoint p. Pixel q is given by the Gaussian G(||p q||), where σ is a neighborhood-size determining factor. Bilateral filters weight neighboring pixels like Gaussian convolution. However, the bilateral filter smooths while preserving edges by considering nearby pixels' value differences. The bilateral filter for the image I is indicated by BF[I], where Iq is the image pixel and Ip is the image midpoint.:

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

Wp functions as a normalization parameter to ensure that pixel weights add up to 1

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

With the parameters σs and σr in the equations, we may determine the amount of filtering applied to the image I in Eq. (3)

2.2. Base Model Architecture

The Deep Convolutional Neural Network-Long Short-Term Memory (Deep CNN-LSTM) model was used as the base model in this study (see **Figure 3**). Two convolutional layers, two maxpooling layers, and two fully connected layers make up the CNN model structure. In order to function, the CNN and LSTM models convert the CNN output to (batch size, H, W*channel), where H and W stand for the image's height and width, respectively. This will provide the LSTM layer access to data in 3D. The reshape procedure is triggered by the lambda function. Layers of dense and softmax activation functions are employed by the LSTM model to make its predictions. The used LSTM layers each had 16 and 96 units. The output of the LSTM layer is then sent to the fully connected (FC) output layer, which is activated using a Softmax function, for final classification.

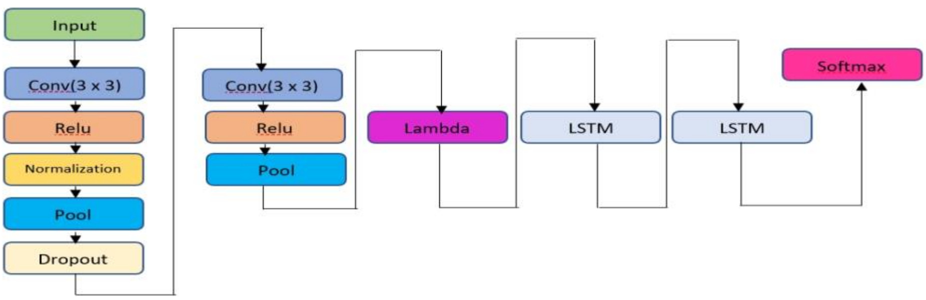

Figure 3. *Architecture of CNN-LSTM*

2.3. Dynamic Selection Scheme for Horizontal Voting Ensemble

Algorithm A describes the suggested method for selecting members of the horizontal voting ensemble dynamically. While training the base learner on the training set, the approach dynamically determines competent models based on the validation accuracy measure, allowing for the construction of a horizontal voting ensemble for prediction. Each training epoch is saved if model accuracy is over the threshold. To build a prediction ensemble, the ideal subset of stored models is chosen depending on ensemble size. Dynamic selection allows the best-performing models to join the ensemble during prediction, unlike the current technique in which ensemble members are deliberately chosen. Algorithm A describes the process.

Algorithm A: Dynamic stage

Input

Dataset: $Data_{set} = Data_{Trn}$ U $Data_{Test}$

Component $Data_{set}$ Intersection in $Data_{Trn}$ & $Data_{Test} = \emptyset$

Set initial values for J,j and K_{set}

Set list $En_{j=}$ [ ]

Set selection *threshold_value*

Procedure

While i ≤ J **do**

Train $Data_{Trn}$ for one epoch

if $epoch_{Acc} \geq$ *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 K_{set} to En_j where j is the first j^{th} elements of K_{set}

Output: En_j, j

The dynamic technique was used at two critical times in the development of the model. When choosing ensemble members and a single classifier's output surpasses the ensemble forecast, respectively.

The second algorithm dynamically selects a final prediction classifier. Algorithm B received ensemble member from algorithm1. The experiment used up to 150 epochs with ensemble sizes from 1 to 50. It provides the general dynamic selection method to horizontal voting ensemble. The dynamic technique was used in two key model development periods. First, when choosing a model for the ensemble, and second, when determining which classifier or ensemble score gives the best prediction score.

Algorithm B: Final Phase of DHV Ensemble 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}

3. Experimental Results

Table 2 illustrates the trained DHVE model's accuracy, precision, recall, and F1 score. Image quality and assessment methodologies impact algorithm performance measurement.

Table 2. *Classification performance of the DHVE model*

Fingerprints	Precision	Recall	F1 Score	Support
Adult	0.94	0.95	0.95	170
Child	0.77	0.76	0.75	170
Senior	0.79	0.74	0.74	170
Teen	0.99	1.00	0.99	170

From **Table 2**, The classification performance for teen in terms of recall equal to 1. The recall score of 1 signifies that all True Positives were identified and classified correctly. The precision and F1 score for Teen are near 1 at 0.99. This means that almost all the positive samples are classified to be positive and non-positive samples are classified as non-positive samples (for Precision values equal to 0.99). The F1 score of 0.99 means that the model was able to classify imbalance data perfectly. The DHVE model overall accuracy score for Age Group classification is 91% as shown in **Table 3**.

Table 3. *Overall Classifications Performance of DHVE model*

Classification Parameter	Precision	Recall	F1-Score	Support
Accuracy			0.91	680
macro avg	0.91	0.91	0.91	680
weighted avg	0.91	0.91	0.91	680

From **Table 3**, the macro and weighted average precision, recall, and F1 Score is 0.91, 0.91, and 0.91 respectively. Each metric performs well in classification. The macro and weighted average F1 score of 0.76 suggests that the proposed model effectively classified imbalance dataset. See **Figure 4** for the Average ROC-AUC.

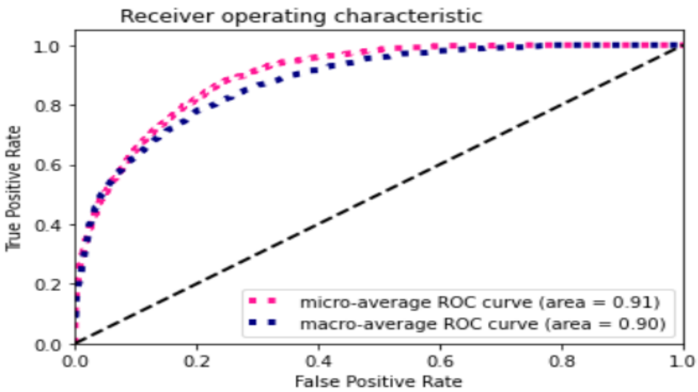

Figure 4. *Average ROC-AUC Plot of the DHVE Model for Age Group Classification*

Figure 4 depicts the average Receiver Operator Characteristics (ROC) Curve of the DHVE Model for multi-class. It depicts the Probability-based Curve that graphs the TPR vs the FPR at different levels, effectively isolating noise. The Area Under the Curve (AUC) measures the classifier's ability to distinguish across classes. The bigger the values, the stronger the classifier's ability to distinguish between positive and negative categories. Comparing the number of true positives against the rate of false positives, the Receiver Operating Characteristic (ROC) curve illustrates how effectively a model can classify. **Figure 4** illustrates the micro and macro averages for all examined classes. As seen by the average curve (across all classes), the model distinguishes between positive and negative classes with outstanding precision, as class averages are close to 1.00. **Figure 5** depicts the Confusion matrix for the DHVE classification.

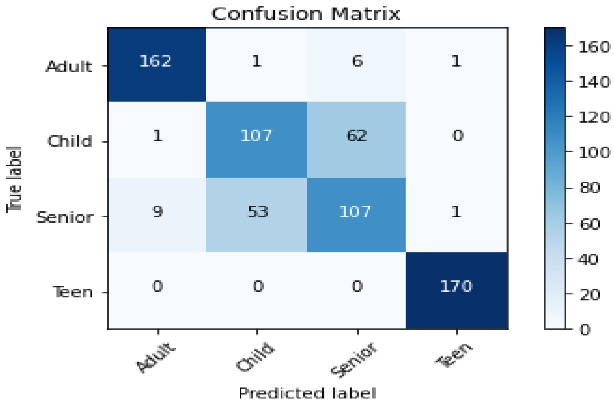

Figure 5. *Confusion Matrix of the DHVE Model for Age group*

Figure 5 illustrate the Confusion matrix for each Age group classification. The actual and predicted values for Adult, Child, Senior, and Teen are 162, 107, 107 and 170 respectively. The Confusion matrix for each class shows that the actual and predicted value for all Teen were correctly classified at 170. The model predicted 162 as Adult correctly while 1,6,1 Adult images were wrongly predicted as Child, Senior and Teen respectively. Likewise, 107 Child and 107 Senior were correctly classified. The model misclassified 62 Child as Senior, 9 Senior were wrongly classified as Adult. **Figure 6** shows the accuracy distribution of the proposed DHVE model with HVE and CNN-LSTM model.

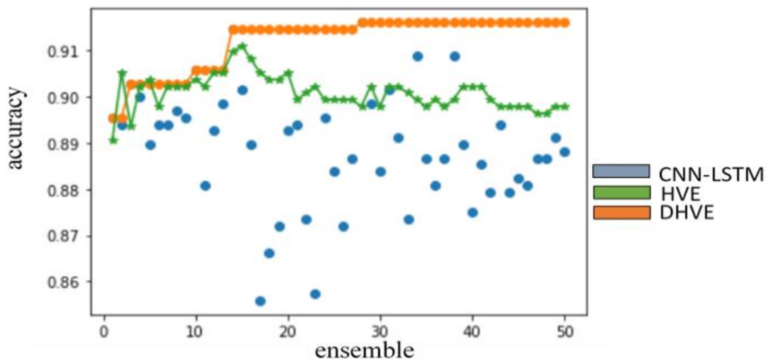

Figure 6. *Line Plot showing DHVE Performance comparison with other Model*

Figure 6 shows the accuracy distribution of the proposed DHVE model with HVE and CNN-LSTM model. The Blue legend in the plot is the result for CNN-LSTM and the Green is the HVE, Orange is the result for DHVE. The accuracy for CNN-LSTM, HVE and DHVE models are 0.878, 0.897 and 0.912 respectively. From **Figure 6**, the HVE and DHVE curves shows the performance of the ensemble models of various sizes from 1-50 members. The DHVE curve reveals that the performance of the ensemble improves as the number of ensemble increases from 12 until somewhere around 25 ensemble size where the performance became stable. The plot also reveals that the dynamic approach, which allow best performing models to participate in the prediction, enhances the performance of DHVE as against HVE in green colour which uses the static ensemble selection. The DHVE model outperforms all the other models with overall accuracy of 0.912. **Table 4** shows the performance metric of the models.

Table 4. *Models Performance on Precision, recall, F1 and Accuracy Metrics*

Models	Performance Metrics (%)			
	Precision	Recall	F1 Score	Accuracy
CNN-LSTM	88.0	87.0	87.0	87.0
HVE	89.0	87.0	87.0	89.0
DHVE	91.0	91.0	91.0	91.0

The superior performance of the DHVE model relative to other models demonstrates that the incorporation of a dynamic scheme increases the accuracy of the final prediction.

3.1. Comparison with existing networks

The performance of the proposed DHVE model was compared to that of k-Nearest Oracle algorithm (KNORA) and Dynamic Classifier Selection with Overall Local Accuracy (DCS-LA) algorithm using the data obtained for this study. DCS-LA algorithms that decide on a trained model from a large pool of candidates depending on the specifics of the input The k-nearest neighbor (kNN) approach is used to locate the k most comparable instances from the training dataset which correspond to the example when a prediction is needed. Evaluation of each model's classification accuracy on the vicinity of k training examples is known as local accuracy (OLA) [21]. The model chosen to make a forecast for the new example is the one that performs the best in this region. KNORA model is a dynamic selection-based oracle-based approach presented by [22]. The KNORA model's neighborhood boundaries are determined by the k-nearest neighbor's algorithm's parameters. Choosing a k number that fits the dataset is crucial since it determines the neighborhood size. When k is too little, relevant training set samples may be removed from the neighborhood, but when k is too huge, relevant samples may be masked by too many instances. This experiment tests ten different k values from 2 to 12 to get the optimum dataset outcome. This experiment will use the KNORA–Union algorithm. **Figure 7** and **8** illustrates KNORA-U and DCS-LA model accuracy distribution on age group dataset with k values from 2 to 12.

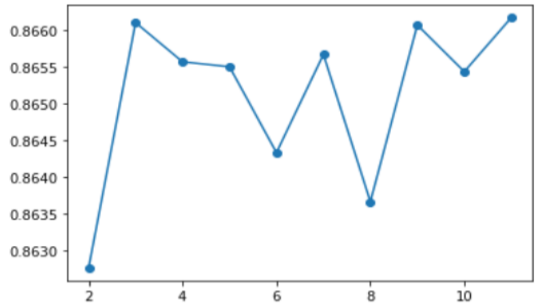

Figure 7. *Line Plot Showing Age Group Dataset Accuracy Distributions for KNORA-U*

The minimum performance occurs when k = 2, while the maximum accuracy is 0.866% at neighborhood size of k = 3 and 11.

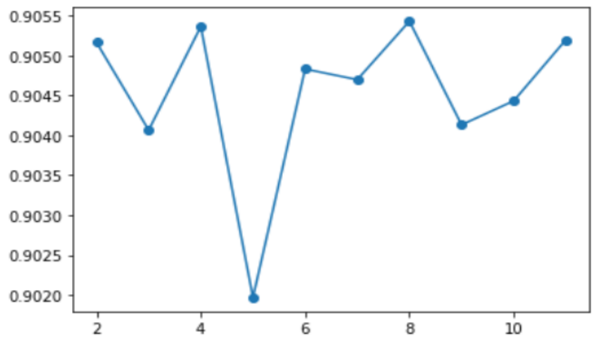

Figure 8. *Line Plot Showing Age Group Dataset Accuracy Distributions for DCS-LA*

The minimum performance occurs when k = 5, while the maximum accuracy is 0.90% at neighborhood size of k = 8

Table 5. *Comparison of proposed DHVE with KNORA-U and DCS-LA model.*

Dataset	Model Accuracy (%)		
	KNORA-U	DCS-LA	DHVE
Age group	86	90	91

4. Conclusion

Based on the outcomes of this study, a model has been developed that can determine age group estimations using fingerprint data. In addition, the results of this research have shown, via a series of controlled experiments, that the implementation of a dynamic scheme results in an improvement in the functionality of the horizontal voting ensemble method. The study's results also show that the DHVE Model is a good tool for recognizing fingerprints in a biometric system. Others advantages of this study shows improvement in the accuracy of the predictions. It reduces the variance of the predictions and makes the predictions more robust to noise. Based on how well the model worked, fingerprints could be put into groups based on age with little error. the disadvantage It is computationally expensive compare to known ensemble model. Training the model with a larger dataset can help it do a better job of classifying. In the future, researchers could also look into how adaptive preprocessing techniques could be used to improve low-quality fingerprint images and make classification models more accurate.

Declaration of interest: The authors declare that there is no conflict of interest.

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