ETHNICITY CLASSIFICATION USING A DYNAMIC HORIZONTAL VOTING ENSEMBLE APPROACH BASED ON FINGERPRINT

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Abstract: Today, there is a fierce rivalry between ethnic groups in Nigeria on a number of issues, such as the division of power and resources, aversion to dominance, and uneven growth. Ethnicity as an identity naturally occupies a prominent position in the political arena. It is the simplest and most natural way for people to mobilize around essential human needs such as security, food, shelter, economical well-being, inequity, land distribution, autonomy, and recognition. Recent research has revealed the potential to determine an individual's ethnicity based on biometric data automatically. These studies reported significant advancements in automatically predicting demographics based on facial and iris traits. This success has been ascribed to the availability of a sufficient amount of high-quality data. There needs to be more data about the likelihood that fingerprints can disclose an individual's ethnicity. A need for more data causes this difficulty. This study aims to obtain fingerprint pictures via live scan among the major ethnic groups in Nigeria. For training and classification of the fingerprint images, the proposed Dynamic Horizontal Voting Ensemble (DHVE) deep learning with a Hybrid of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) as the base learner was employed. Standard performance classification metrics such as Accuracy, Recall, Precision, and F1 score were used to evaluate the performance analysis of the model. This study demonstrated an accuracy of over 98% in predicting a person's ethnicity. Additionally, the proposed model outperformed existing state-of-the-art models.

Keywords: Biometric, deep learning, demographic, ethnicity, fingerprints.

I. INTRODUCTION

An ethnic group or ethnicity has been defined as a social class of individuals who share a cultural, ancestral, social, and general experience-based identity [1]. They are individuals recognized as distinct communities due to their unique characteristics that distinguish them from other adjacent communities. Certain traits shared by an ethnic group include culture, religion, language, and other forms of traditions that contribute to a group's distinctiveness. In the last decade or two, ethnic conflict has increasingly dominated worldwide political discourse. Events such as those occurring in Rwanda, Burundi, and the Balkans have elevated the issue to a prominent position. Still, it is hardly new, as several examples in Africa demonstrate. Polarization between ethnic groups and fighting over resources, political and economic power, and other purposes has led to genocide, ethnic cleansing, and civil war.

Nigeria, located in West Africa, is the continent's most populous nation, with around 200 million people [2]. Rich in oil reserves and other natural resources, Nigeria is one of the most developed African states. Still, persistent conflicts of interest between diverse ethnic groups have stifled Nigeria's political and economic growth. Nigeria was established in 1914 as a multiethnic nation comprised of more than 200 ethnic groups speaking more than 250 languages. The three largest ethnic groups are Hausa-Fulani, Yoruba, and Igbo, who comprise around 28%, 20%, and 17% of the population, respectively. Today, in Nigeria, there is intense competition between ethnic groups over various concerns, including the distribution of power and resources, the fear of dominance, and uneven growth. Ethnic Identity is one of the essential requirements listed by the basic needs theory for Nigeria to advance democratically, economically, and politically since it is an exceptionally potent motivator for social mobilization. Ethnicity as an identity naturally occupies an important place in the political arena, and it is also the simplest and most natural method for people to mobilize around fundamental human needs such as safety, food, shelter, economical well-being, inequality, land distribution, autonomy, and acknowledgment [3].

Recent research has uncovered the capability of automatically determining an individual's ethnicity from biometric data [4]. Face and iris modalities have been extensively examined for their ability to indicate an individual's ethnic group. It is difficult for machines to establish an individual's ethnicity based on facial characteristics, although humans can do so easily [5]. These researchers noted that tremendous progress had been made in automatically predicting demographics from facial and iris features. This accomplishment has been attributed to the availability of a sufficient quantity of data and the excellent quality of the data. Numerous face-based ethnicity classification techniques have been developed, including universal face analysis, feature extraction, 3D model methodology, and periocular feature fusion [6].

Researchers uncovered a mathematical relationship between fingerprint pattern kinds, ethnicity, and the finger on which they occur in one of the earliest studies to examine the possibility of ethnicity identification based on fingerprint features [7]. The study observed the process of fingerprint development in a fetus and suggests that fingerprint pattern types are likely an inherited trait, even though each inheritable type is unique. Two thousand fingerprint records from the Athens/Clarke County Police Department (Georgia) database were reviewed to test the hypothesis. Considered were the White, Black, Asian, and Hispanic populations. Mathematic calculations were utilized to compare the patterns of each race and each finger. The results demonstrated that specific fingerprint patterns occurred in every race. However, certain fingerprint patterns dominated certain races more than others. For example, whorls are more prevalent in the fingerprints of Asians than those of other ethnicities, whereas loops and arches are more prevalent in the fingerprints of Blacks. In Whites and Hispanics, other different patterns tend to predominate. The findings demonstrate the relationship between fingerprint pattern types, ethnicity, and the finger on which they appear.

According to an early study conducted on fingerprint characteristics for people of Nigerian descent [8]. This study demonstrates the variation in the frequency of the arch, loop, and other fingerprint pattern types among Nigeria's varied ethnic groups. A survey of the fingerprint pattern of the Ogoni[9] examined the frequency of pattern types among Nigeria's various ethnic groups. Another study was carried out to investigate pattern-type frequencies in the Ijaw ethnic group[10]. In a similar study, Random amplified polymorphic D.N.A. (RAPD) was employed in fingerprinting approach based on Polymerase Chain Reaction (PCR) to determine genetic differences between people from the three largest ethnic groupings in Nigeria (Hausa, Igbo, and Yoruba) [11]. The study revealed that Hausa's fingerprinting pattern using the open-label clinical trial OPC2 differs significantly from those of Igbo and Yoruba. Fingerprint patterns of two Nigerian ethnic groups were compared in another study [12]. A case study of the Itsekiri and Urhobo ethnic communities in Warri, South Southern Nigeria is discussed. The results revealed that Itsekiri females and Urhobo males had the ulnar loop fingerprint pattern, whereas Itsekiri males and Urhobo females had the whorl and arch fingerprint patterns.

In a study conducted to assess the demographic distribution of fingerprint minutiae in two Nigerian ethnic groupings, the biometric information of forty-four (44) Igbo and forty-four (44) Yoruba individuals were gathered utilizing a hand impression approach using an ink pad and paper. The obtained fingerprints were examined using a hand lens. The many types of minute details under examination were tallied as they appeared on each fingerprint. Using Fisher's exact test and univariate analysis in SPSS 21 with a significance level of 0.053, the statistical significance of the variance in the number of specifics among the various ethnic groups was studied. Bifurcations and convergences account for 54.85% of the study's Total Minutiae Counts (T.M.C.). The research indicated that the Igbo ethnic group consistently had a more significant number of all minutiae types.

In an experiment, feature extraction approaches determine a person's ethnicity using fingerprint biometrics and deep learning [13]. To this end, 1054 fingerprint images of Nigerians from three distinct ethnic groups (Yoruba, Igbo, and Middle Belt) were collected. Kernel Linear Discriminant Analysis (KLDA) and Kernel Principal Component Analysis (K-PCA) were used to extract features. CNN was utilized for supervised learning and categorization of the features. The classifier categorized eight (8) as Yoruba, forty-eight (48) as Igbo, and four (4) as Hausa based on the findings of an experiment in which just sixty individual fingerprints were evaluated. K-PCA and KLDA achieved a Recognition Accuracy of 93.97 and 97.26 percent, respectively. Recognition accuracy is the ratio of correct predictions to total input samples. K-Average P.C.A.'s Recognition Time was 9.98 seconds, whereas KLDA's was 10.02 seconds. T-Test paired sample statistics were used to analyze the given result, which demonstrates that KLDA is superior to K-PCA in terms of Recognition Accuracy. In terms of computation time analysis, KPCA is less expensive than KLDA because of its faster processing speed. Though little research has been conducted to determine the likelihood of an automatic ethnicity recognition and authentication system using fingerprint biometrics, there is ample evidence that an individual's ethnicity can be recognized automatically using fingerprint biometric data. [14-15].

In conclusion, most earlier publications analyzed ridge characteristics for categorization purposes, while some employed the ink approach for fingerprint capture. Human error is unavoidable during the data collection procedure, which poses a challenge for this method. Similarly, an insufficient data set is a crucial drawback, making it impossible to generalize the results. Most of the research did not investigate the application of the deep learning approach, which can automatically identify and characterize the underlying differences in data that are difficult to measure. This is the motivation for this study, which aims to produce a complete and realistic fingerprint dataset using a live-scan device that considers the subject's ethnicity. The dataset is expected to address the gap identified in this introduction. The proposed system will be implemented with a novel DHVE deep learning model that learns to classify fingerprint images directly.

II METHODS AND MATERIALS

This paper proposes the DHVE model for ethnicity classification using fingerprint images. As shown in Figure 1, the proposed model framework has four phases. The first phase consists of data collection and pre-processing, the second involves model building and training, the third phase is the dynamic ensemble selection, and the fourth is the prediction phase.

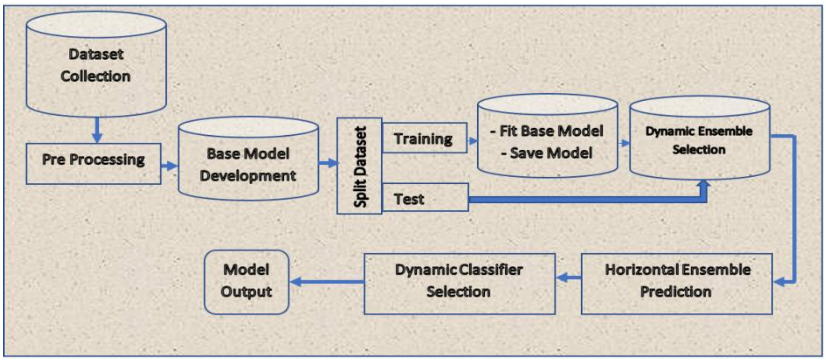

Fig. 1 Dynamic Horizontal Voting Ensemble Framework

A. Data Collection

In this study, 450 Nigerian subjects had their fingerprints captured. Each participant's ten (10) fingerprints were obtained, resulting in a total sample size of 4,500 images. Table 1 illustrates the fingerprint image distribution for the ethnicity experiment. Out of the 4500 fingerprints captured, 1620 were from Hausa, 1380 were from Igbo, and 1500 were from Yoruba. To ensure dataset fairness and balance, only 1380 subset images from Hausa and Yoruba subjects were used for the experiment (See Table 1).

TABLE. 1 Dataset distribution according to ethnicity

Biometric Class	Training Set	Test Set	Total
Hausa	1,104	276	1,380
Igbo	1,104	276	1,380
Yoruba	1,104	276	1,380
Total	3,312	828	4,140

As shown in Figure 2, the fingerprint images were tagged with information such as image I.D., gender, age group, ethnicity, and finger type labels (thumb, index, middle, ring, and little finger labels). The various subjects belong to the three major ethnic groups in Nigeria (Hausa, Igbo, and Yoruba).

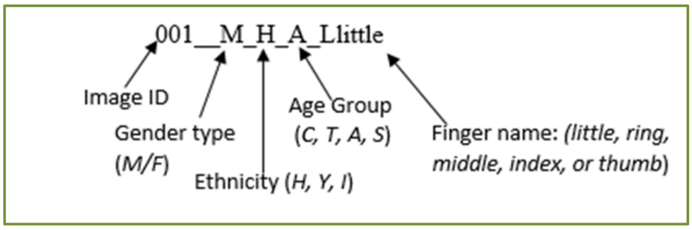

Fig. 2 Fingerprint image attribute

B. Data Preprocessing

Images acquired during the fingerprint capture phase are often grayscale and susceptible to noise due to environmental and physical factors that affect the user's skin. Such images are consequently unsuitable for appropriate image processing. Processing fingerprint image recognition relies on the quality of fingerprint images. It has been demonstrated that the quality of the fingerprint image dataset significantly impacts the model's performance; therefore, image preprocessing is essential while training deep learning models [16]. Image enhancement may be required due to environmental factors such as wetness, which can affect the dry or wet nature of the fingerprint, or a lack of image contrast, which might result in insufficient image features [17].

Preprocessing aims to reduce noise and eliminate undesirable features and distortions, enhancing the quality of acquired fingerprint images. The noise-free image produced via fingerprint preprocessing yields superior results from the applied model. Image preprocessing is, therefore, a crucial stage in fingerprint identification systems. This study initially utilized the histogram equalization technique to improve fingerprint image collection. It is the technique of transforming an image's histogram into a uniform histogram by introducing a complete selection of grey levels uniformly across the image's histogram [18]. It is the process of adjusting image intensities to improve contrast. The histogram is defined for a given image f represented as an *mr* by *mc*-dimensional matrix with pixel intensities ranging from 0 to L-1. L represents the number of potential intensity values, which is typically 256. Let p be the normalized histogram of f's probabilistic intensities. So

$$pn = \frac{\text{number of pixels with intensity } n}{totalnumberofpixel \quad !} \quad \text{where } n = 0, 1, \ldots \text{L-1}. \tag{1}$$

The histogram equalized image g will be defined by

$$g_{i,j} = \text{floor}((\text{L} - 1)\sum_{n=0}^{f_{ij}} p_n), \tag{2}$$

where *floor()* slices down to the adjoining integer. A bilateral filter was then used to smooth and denoise the image while preserving the edges. A bilateral filter is superior to other filtering algorithms due to its simplicity of formulation, dependence on minimal parameters, often two parameters denoting size and contrast, and fast computational speed [19]. The bilateral filter is an improvement over the Gaussian filter, which frequently obscures critical edge information by blurring everything, regardless of whether it is noise or an edge. The formula for Gaussian blurring can be expressed as follows:

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

where G.B. [x] represents the Gaussian kernel in two dimensions. Gaussian filtering acts by computing the pixel intensity weighted average of neighboring spots with a diminishing weight pattern to the spatial distance from the midpoint p. Pixel q is defined by the Gaussian G(||p q||), where σ is a neighborhood-size characterizing factor. Similar to Gaussian convolution, the bilateral filter is a weighted average of adjacent pixels. In contrast, the bilateral filter preserves edges while smoothing by considering the value difference between neighboring pixels. The bilateral filter for image I is indicated by B.F. [I], where Iq is the image pixel, and Ip is the image midpoint.

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\| p - q) G_{\sigma_r}(I_p - I_q) I_q. \tag{4}$$

where Wp serves as a normalization parameter to ensure that the sum of pixel weights is 1.

$$W_p = \sum_{q \in S} G_{\sigma_s}(\| p - q) G_{\sigma_r}(I_p - I_q) I_q \tag{5}$$

In Eqn. (5), the parameters σs and σr specify the degree of filtering for image *I*.

C. Base Model Architecture

In this experiment, the hybrid Deep Convolutional Neural Network-Long Short Term Memory (Deep CNN-LSTM) model served as the base model (see Figure 3). The CNN model structure consists of two convolutional layers, two max-pooling layers, and two fully connected layers. The CNN and LSTM models work by transforming the CNN output into (batch size, H, W*channel), where H and W represent the height and width of the image, respectively. This will result in 3D data used by the LSTM layer. The lambda function activates the reshape subroutine. The LSTM model is linked to the dense and softmax activation function layers used to generate the final prediction. Each of the LSTM layers utilized contained 16 and 96 units, respectively. For final classification, the output of the LSTM layer is fed into the fully connected (F.C.) output layer with a Softmax activation.

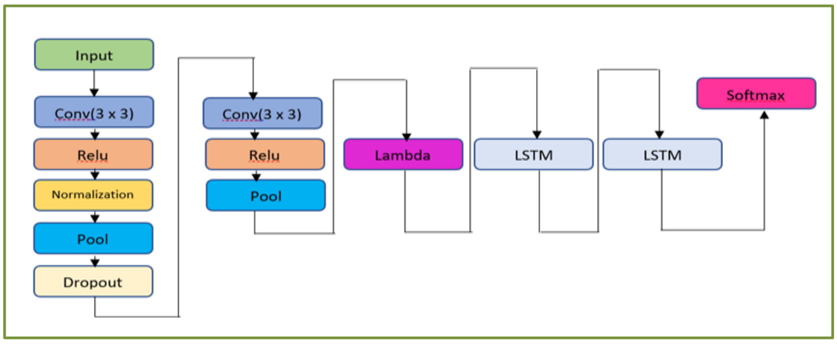

Fig. 3 Architecture of CNN-LSTM

D. Proposed Dynamic Selection Scheme for Horizontal Voting Ensemble

In the conventional horizontal voting ensemble method, ensemble members are deliberately selected from a specified starting point throughout a single run. In contrast, the proposed dynamic ensemble selection method constructs a horizontal voting ensemble for prediction by dynamically selecting competent models based on validation accuracy measures during the base learner training. This strategy allows the models with the best performance to be included in the prediction ensemble. In this experiment, the base model was optimized for 150 epochs with a mini-batch size of 128 and a validation split of 0.2. The proposed approach for dynamically selecting the ensemble member for horizontal voting is illustrated in Algorithm 1. Each training epoch is saved if the model's Accuracy meets or exceeds the predefined threshold. The optimal subset of the saved models is then selected based on the ensemble size desired for prediction. The steps of Algorithm 1 are noted down.

Algorithm 1. Dynamic ensemble selection phase

Input
Data: $D_{set} = D_{Trn} \cup D_{Test}$, $D_{Trn} \cap D_{Test} = \emptyset$
Parameters: N, n
Initialize K_{member}, $E_{n} = [\ ]$
Initialize *threshold*
Procedure
    for all i in range N:
        Use D_{Trn} for one epoch training
        if $Model_{Accuracy} \geq threshold$:
         model.save(filename(i))
      end for
K_{member} = load_all_model saved
Sort $K_{member}$by $Model_{Accuracy}$
for i in range (1, n):
        $E_n = E_n \cup K_{member}(i)$
end if
Output: E_n, n

The second algorithm displays the dynamic selection of a classifier for the final prediction. The ensemble member generated by algorithm1 was given as input to algorithm2.

Algorithm 2. Dynamic horizontal voting ensemble

Input: Trained n members models for voting ensemble En= {e1,..en} and evaluate on
test datasets $D_{test} = \{Dt_1,..,Dt_5\}$
Ensemble score En_{score},
Initialization: Preds, $Model_{scores} = [\ ]$
Initialization: $Model_{max}$, Subset, Single_Score
Procedure
    for all i in range n:
        Subset = En[:i]
        if iteration <= i then
        Put D_{test} into Subset(iteration), get softmax output vector predi
        Add predi to Preds
        Iteration = iteration + 1
        end if
        Pred =
        En_{score} = argmax(Pred)
        for j in range (1, i+1):
                Single_Score = En[j-1]. predict(D_{test})
                $Model_{scores}$=$Model_{scores}$Single_Score
         end for

Iteration = 1
end for
$Model_{max}$ = max($Model_{scores}$)
If $Model_{max}$ outperformEn_{score} then En_{core} = Model $_{max}$
Output: En_{core}

The experiment utilized a maximum of 150 epochs, with ensemble sizes ranging from 1 to 50. Algorithm 2, therefore, gives the general algorithm for the dynamic selection approach to the horizontal voting ensemble. The dynamic system was utilized at two important phases in the model's development. The process is, at first, when selecting which model to include in the ensemble and second, when assessing which of a single classifier or the ensemble score yields the best prediction score.

III RESULTS AND DISCUSSION

The Accuracy, Precision, Recall, and F1 score of the DHVE model after training on the Ethnicity classification of Hausa, Igbo, and Yoruba are shown in Table 2.

TABLE 2. Classifications Performance of DHVE Model

Fingerprints	Precision	Recall	F1-Score	Support
Hausa	0.98	0.96	0.97	276
Igbo	1.00	0.99	0.99	276
Yoruba	0.97	1.00	0.98	276

According to Table 2, Igbo classification performance has a precision of 1. This implies that all positive samples are classed as positive, while non-positive samples are categorized as non-positive (for Precision values equal to 1). The classification performance of Yoruba has an F1 score of 1, indicating that the model correctly classified imbalanced data. The DHVE model's overall classification accuracy is 98%, as reported in Table 3.

TABLE 3. Overall Classifications Performance of DHVE model

Classification Parameter	Precision	Recall	F1-score	support
Accuracy			0.98	828
macro avg	0.98	0.98	0.98	828
weighted avg	0.98	0.98	0.98	828

Figure 4 depicts the Confusion Matrix. Actual and expected values for Hausa, Igbo, and Yoruba are 266, 271, and 276, respectively. The Confusion matrix for each class demonstrates that all Yoruba's actual and expected values are 276. The model accurately identified 266 as Hausa but incorrectly identified nine as Yoruba. Similarly, 271 Igbo were correctly classified, whereas 5 Hausa were incorrectly categorized.

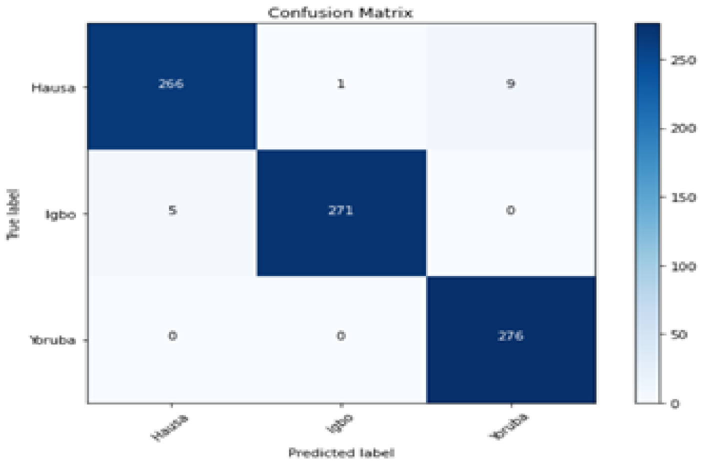

Fig. 4 Confusion Matrix of the proposed DHVE Model for Ethnicity classification

Figure 5 depicts the Average Receiver Operator Characteristics (R.O.C.) Curve for the DHVE Model's ethnicity classification. It displays the Probabilistic Curve, which plots the T.P.R. against the F.P.R. at various threshold values and effectively separates noise. Area under this curve (A.U.C.) indicates the model's performance under consideration. The closer A.U.C. is to 1, the more efficient the model is. The micro and macro averages for each of the classes under investigation are depicted in Fig. 5. As seen by the average curve (across all classes), the model distinguishes between positive and negative classes remarkably well, with class mean values close to 1.00.

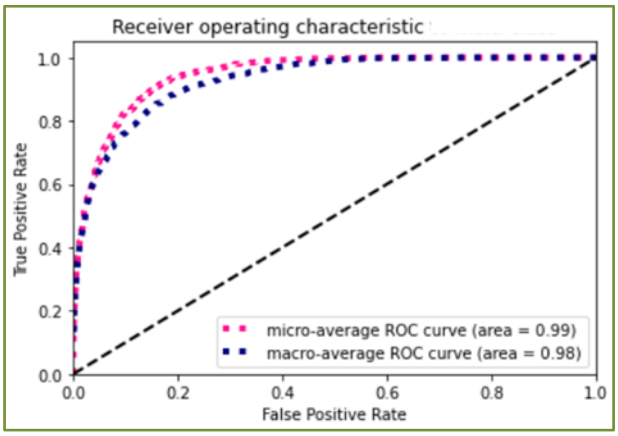

Fig. 5 Average ROC-AUC Plot of the DHVE Model for Ethnicity Classification

Figure 6 compares the performance of the proposed DHVE model to that of the CNN-LSTM and H.V.E. models. The Blue legend represents the CNN-LSTM result, the Green legend represents the H.V.E. result, and the Orange legend represents the DHVE result. The Accuracy of the CNN-LSTM, H.V.E., and DHVE models is 0.977, 0.982, and 0.984, respectively. The flattening of the DHVE plot indicates that the model is stable. Hence any ensemble size greater than 20 for the DHVE model is still a viable option for prediction. With an overall accuracy of 0.984%, the DHVE model outperforms all other models. Table 4 displays precision, recall, F1 score, and Accuracy for classification models based on ethnicity.

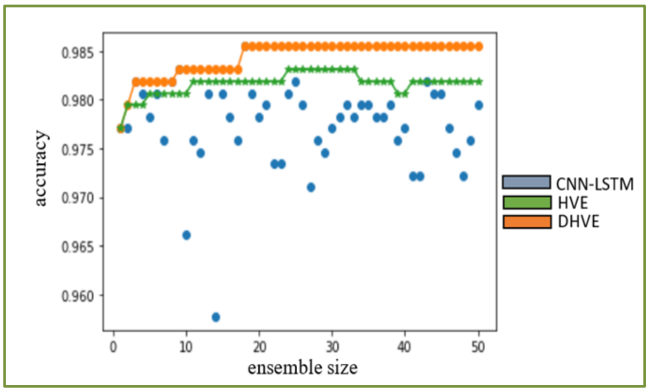

Fig. 6 Line plot showing the performance comparison of DHVE with other Models for

TABLE 4. Precision, recall, F1, and Accuracy for models on Ethnicity classification

Models	Performance Metrics (%)			
	Precision	**Recall**	**F1 Score**	**Accuracy**
CNN-LSTM	97.0	97.0	98.0	97.0
HVE	98.0	98.0	98.0	98.2
DHVE	98.0	98.0	98.0	98.4

Using the dataset collected for this investigation, the performance of the proposed DHVE model was compared to that of KNORA. KNORA algorithm is a dynamic selection-based oracle-based method that was proposed by (Ko et al., 2008). The KNORA model depends on the parameters of the k-nearest neighbor's algorithm since it determines the neighborhood borders within which each ensemble is evaluated. Because it defines the neighborhood's size, selecting a k value acceptable for the dataset being used is vital. When the value of k is too small, relevant samples from the training set may be excluded from the neighborhood, but when the value of k is too big, relevant samples may be masked by excessive examples. This experiment examines ten (10) diverse values of k ranging from 2 to 12 to identify the optimal result on the dataset. This experiment will implement the KNORA–Union variant of the KNORA algorithm. Figure 7 shows the accuracy distribution of the KNORA-U model on the ethnicity dataset with varying values of k from 2 to 12

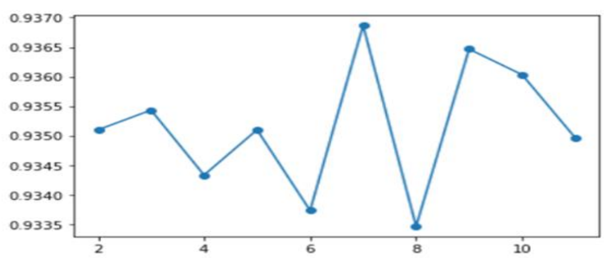

Fig. 7 Line Plot Showing Accuracy Distributions for k Values in KNORA-U

The minimum performance occurs when k = 8, while the maximum Accuracy of 0.937% occurs when k = 7.

TABLE. 5 Comparison of proposed DHVE with KNORA-U model

Dataset	Model Accuracy (%)	
	KNORA-U	**DHVE**
Ethnicity	93	98

IV. CONCLUSION

The basic needs theory identifies ethnic Identity as one of the essential requirements for a society to progress democratically, economically, and politically because it is an exceptionally powerful motivator for social mobilization. This makes ethnic Identity one of the essential requirements for a society to advance democratically, economically, and politically. It is also the most accessible and natural manner for people to organize themselves to address essential human needs such as safety, food, shelter, economic well-being, inequity, land distribution, and autonomy. Using a deep learning method, this study aims to demonstrate the possibility of identifying a person's ethnicity from their fingerprint images. The study's findings showed that determining an individual's ethnicity is possible and effective by analyzing their fingerprint images.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study

REFERENCES

[1]. A. Olasunkanmi, “Ethnic Identity and Constitutional Reprentative Governance in Nigeria,” OALib, vol. 06, no. 07, 2019, pp. 1–9.

[2]. G. Martin and A. Thomson, “An Introduction to African Politics,” African Studies Review, vol. 44, no. 3, 2001. pp. 186.

[3]. F. Kush, “Precolonial Music in Nigeria,” Academia Letters, 2021.

[4]. D. Bobeldyk and A. Ross, “Predicting Soft Biometric Attributes from 30 Pixels: A Case Study in NIR Ocular Images,” IEEE Winter Applications of Computer Vision Workshops, 2019, pp. 1-9.

[5]. S. Gutta, J. R. J. Huang, P. Jonathon and H. Wechsler, “Mixture of experts for classification of gender, ethnic origin, and pose of human faces,” IEEE Transactions on Neural Networks, vol. 11, no. 4, 2000, pp. 948–960.

[6]. H. Chen, M. Gao, K. Ricanek, W. Xu and B. Fang, “A Novel Race Classification Method Based on Periocular Features Fusion,” International Journal of Pattern Recognition and Artificial Intelligence, vol. 31, no. 08, 2017, pp. 1-21.

[7]. A. Kumar, M. Prasad, S. Kumar, P. Kumari and N. Goel, “Study of fingerprint patterns among Medical students in IGIMS, Patna, Bihar,” Journal of Medical Science and Clinical Research, vol. 6, no.12, 2018, pp. 772-776.

[8]. U. U. Akpan, T. Awe, D. O. Idowu and K. O. Adekoya, "Types and frequency of fingerprint minutiae in individuals of Igbo and Yoruba ethnic groups of Nigeria," Ruhuna Journal of Science, vol. 10, no. 1, 2019, pp. 77-87.

[9]. B. N. R. Jaja, O. Olabiyi and C. C. Noronha, "Dermatoglyphics of the Ogoni of Nigeria and its historiographic implications," AnthropologischerAnzeiger, vol. 68, no. 2, 2011, pp. 175–183.

[10]. T. M. Otobo and R. Tarimobo-Otobo, "Digital And Palmer Dermatoglyphic Characteristics of the ijaw Ethnic Group," International Journal of Forensic Medical Investigation, vol. 2, no. 1, 2016, pp. 25-30.

[11]. A. B. Owolabi, "Ethnic Identity, Social Class and Consumption Pattern Among Three Major Ethnic Groups in Nigeria," Advances in Social Sciences Research Journal, vol. 1, no. 5, 2014, pp. 149–159.

[12]. E. J. Jaiyeoba-Ojigho, I. E. Odokuma and P. S. Igbigbi, "Comparative Study of Fingerprint Patterns of Two Ethnic Groups: A Nigerian Study," Journal of College of Medical Sciences-Nepal, vol. 15, no. 4, 2019, pp. 270–275.

[13]. H. O. Aworinde, A. O. Afolabi, A. S. Falohun and O. T. Adedeji, "Performance Evaluation of Feature Extraction Techniques in Multi-Layer Based Fingerprint Ethnicity Recognition System," Asian Journal of Research in Computer Science, 2019, pp. 1–9.

[14]. E. M. Agwu, "Lifestyle Behaviours, Among University Students in Nigeria by Gender and Ethnicity," RA Journal of Applied Research, vol. 04, no. 06, 2018, pp. 1746-1756.

[15]. A. H. Oluwatobi and O.F.W. Onifade, "A Soft Computing Model of Soft Biometric Traits for Gender and Ethnicity Classification," International Journal of Engineering and Manufacturing, vol. 9, no. 2, 2019, pp. 54–63.

[16]. D. Giveki, "Improving the Performance of Convolutional Neural Networks for Image Classification," Optical Memory and Neural Networks, vol. 30, no. 1, 2021, pp. 51–66.

[17]. B. Rim, J. Kim and M. Hong, "Gender classification from fingerprint images using deep learning approach," Proceedings of the International Conference on Research in Adaptive and Convergent Systems, 2020, pp. 7-12.

[18]. B. Pandya, G. Cosma, A. A. Alani, A. Taherkhani, V. Bharadi and T. M. McGinnity, "Fingerprint classification using a deep convolutional neural network," 4th International Conference on Information Management, 2018. pp. 86-91.

[19]. Z. Xuan, H. Liu, C. Li, and Y. Liu, "Wavelet Bilateral Filter Algorithm-Based High-Frequency Ultrasound Image Analysis on Effects of Skin Scar Repair," Scientific Programming, vol. 2021, 2021. pp. 1–7.