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# NIGERIAN ETHNICITY CLASSIFICATION THROUGH FUSED FEATURES FROM MOBILENET-V2 AND LOCAL BINARY PATTERN GUIDED BY ATTENTION MECHANISM

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**ABSTRACT**

Our face plays a vital role in many human-to-human encounters and is closely linked to our identity. Significant promise exists for the automatic recognition of facial features, opening the door to hands-free alternatives and innovative uses in computer-human digital interactions. Deep learning techniques have led to a notable increase in interest in the field of face picture analysis in recent years, especially in applications like biometrics, security, and surveillance. Due to feature overlaps and dataset under-representation, ethnicity classification in computer vision is still a difficult task, particularly for African populations. This study explores Nigerian ethnicity classification, focusing on the three major groups—Hausa, Igbo, and Yoruba—using a hybrid model that integrates MobileNetV2, Local Binary Patterns (LBP), and an Attention Mechanism. The hybrid model achieved an overall classification accuracy of 87%, significantly outperforming benchmarks, particularly in Igbo and Yoruba classifications. While the Yoruba group demonstrated the highest accuracy, overlaps between Hausa and Igbo highlight areas for refinement. This research advances the field by addressing dataset imbalances, incorporating innovative feature fusion, and improving the inclusivity of computer vision models. It has practical implications for identity verification, security, and demographic research while emphasizing the importance of culturally sensitive AI systems tailored to underrepresented populations. Future work includes expanding datasets, enhancing model architectures, and exploring interdisciplinary approaches to further refine ethnicity classification.

**Keywords**: Ethnicity Classification, Computer Vision, MobileNetV2, Local Binary Patterns, Attention mechanism

## INTRODUCTION

Our identity is intricately tied to our face, playing a crucial role in various human-to-human interactions (Mustapha et al., 2021). The automatic detection of facial characteristics holds substantial potential, paving the way for hands-free options and creative applications in digitalized interactions between computers and humans (Razalli and Alkawaz, 2019). In recent times, the field of face image analysis has witnessed a significant surge in interest, driven by deep learning techniques, particularly in applications such as surveillance, security, and biometrics (Obayya et al., 2022). Facial analysis spans soft biometrics, covering ethnicity, expression, identification, age, and gender. Among these, ethnicity recognition has emerged as a dynamic research field, benefiting from advancements in computer vision (CV) and artificial intelligence (AI) models (Obayya et al., 2022).

Ethnicity classification poses a formidable challenge in CV. The scrutiny of ethnicity based on facial features holds significance in face recognition and CV communities, impacting domains like customs checks, border control, and public security, reflecting its critical role in an era of increasing globalization. Researchers have also focused on balancing datasets to mitigate racial biases that often skew classification results. For instance, strategies like generating synthetic images and applying latent diffusion models have been employed to ensure more equitable representation across racial groups (Wu et al., 2023). Studies have highlighted the impact of pre-processing techniques, such as alignment and pose correction, in enhancing the precision of ethnicity classification models. Furthermore, leveraging multimodal data, including 2D and 3D facial features, has shown promise in addressing challenges such as variations in facial expressions, lighting, and occlusions (Zhou et al., 2022). Traditional approaches, like principal component analysis (PCA), have been integrated with modern deep learning frameworks to balance computational efficiency and classification accuracy (Tsalakanidou et al., 2021). In recent years, addressing biases inherent in facial recognition systems has become a critical focus. By using racially balanced datasets or improving algorithms, researchers aim to reduce disparities in model performance across ethnic groups. Generative techniques, such as GANs, have been instrumental in augmenting data for underrepresented groups, ensuring more robust training models. Advanced loss functions and architectural innovations further contribute to narrowing error rates among ethnic categories (Suresh & Guttag, 2022). Moreover, ethnicity recognition aligns with physical anthropology, constituting a distinctive research branch. Facial features, pivotal in ethnicity analysis, are shaped by various factors such as genetics, environment, and societal influences. The intricate interplay of these factors complicates the classification of ethnicities (Cole et al., 2017). The importance of transfer learning in ethnicity classification was showed by its potential in scenarios with limited training data for minority groups (Wang, Liu, & Zhao, 2021). The explored ethical concerns surrounding ethnicity classification systems were emphasized by the need for transparency and accountability in deploying these systems to avoid misuse and discrimination (Smith, Jones, & Patel, 2023).

Genetic variations, though present, often exhibit limited discernibility among different ethnic groups. The complexity of ethnicity classification arises from the inherent similarity in facial features across various ethnicities, highlighting the challenges in distinguishing between them (Khan et al., 2021). This similarity results from the intricate interplay of genetic and environmental factors contributing to facial diversity within and across ethnic groups. To navigate this complexity, exploring the nuanced relationships between genetics, environment, and societal dynamics becomes crucial, unraveling the intricate tapestry of ethnic facial features.

Addressing the challenges in ethnicity classification in CV requires expanding methodologies and incorporating insights from genetics, anthropology, and sociology. This interdisciplinary approach can lead to more accurate models, shedding light on the nuances of ethnic facial features within the broader field of computer vision. Thus, the application of ethnicity as a soft biometric trait for facial image classification remains a longstanding and challenging task within machine learning (Jilani et al., 2019). The framework of this study draws inspiration from the exploration conducted by Makolo & Dada (2023), shedding light on the perception of the Black race within African and African American communities. Their work highlighted the inadequacy of current models in the Nigerian context due to racial imbalances in existing datasets. In response, the authors curated a distinct dataset, meticulously labeled to accurately represent Nigeria's major ethnic groups: Hausa, Igbo, and Yoruba.

This study focuses on the classification of ethnicity, specifically the three major ethnic groups in Nigeria – Hausa, Igbo, and Yoruba – as discernible demographic traits within facial features. Leveraging a hybrid model, the research builds upon Makolo & Dada's (2023) work, aiming to advance existing methodologies. The proposed approach involves feature extraction using a combination of MobileNetV2 and Local Binary Patterns (LBP), with Attention Mechanism employed for classification. This integration aims to enhance the accuracy and robustness of facial recognition models, particularly in the realm of Black African images, focusing on Nigeria's diverse ethnicities.

The combination of MobileNetV2 and LBP represents a synergy between high-level and low-level feature extraction techniques. MobileNetV2 efficiently extracts complex features, suitable for scenarios with constrained computational resources. On the other hand, LBP, operating as a low-level feature extractor, provides a robust mechanism for capturing fine-grained details and local structures in an image. This combined approach leverages the strengths of both methods, resulting in a powerful and nuanced feature extraction strategy for image analysis tasks (Iqbal et al., 2022; Mubarak et al., 2022).

Hence, the aim of this study is to create a hybrid model that combines MobileNetV2 and Local Binary Pattern, employing Attention Mechanism as the classifier.

## MATERIALS AND METHODS

The study of ethnicity classification, particularly in the Nigerian context, is a critical area of research within computer vision. It aims to leverage advanced deep learning techniques to distinguish among the three major ethnic groups—Hausa, Igbo, and Yoruba—based on facial features. Ethnicity recognition serves as a vital application of artificial intelligence in domains such as security, identity verification, and sociocultural research. However, challenges such as dataset imbalances, feature overlaps among ethnic groups, and biases in existing models hinder the development of accurate and fair classification systems.

Recent efforts, such as those by Makolo & Dada (2023), have explored the classification of Nigerian ethnic groups using pre-trained Convolutional Neural Networks (CNNs) such as ResNet-50, MobileNet v2, EfficientNetB3, VGG-16, and VGGFace for large dataset mostly from imagenet, EfficientNetB3 was used to train their Model. Despite achieving high accuracy for the Hausa ethnic group, the performance for Igbo and Yoruba groups was significantly lower, with accuracies of 56% each. This disparity raises concerns about model robustness, dataset representation, and methodological transparency. Moreover, the used of large pre-trained images mostly from various population across the globe for transfer learning techniques and addressing convergence duration adds to the reproducibility challenges of existing research.

To address these limitations, a hybrid model combining a pre-trained MobileNetV2 and Local Binary Pattern (LBP) with attention mechanism was developed. This model facilitates high-level feature extraction, texture analysis, and enhances classification accuracy for Hausa, Igbo, and Yoruba ethnic groups, Specifically, it focuses on improving performance for underrepresented ethnic groups (Igbo and Yoruba), thereby mitigating issues related to dataset overfitting.

The methodology adapted is underpinned by the creation of a curated ethnicity dataset that reflects Nigeria's diverse ethnic characteristics. Data augmentation techniques are employed to enhance the dataset's robustness, ensuring a wide representation of facial variations in terms of pose, lighting, and background. Evaluation metrics such as precision, recall, F1-score, and ROC-AUC are used to rigorously assess the model's performance, the detailed methodology employed in the development and assessment of the hybrid model for ethnicity classification is elucidated. The overarching goal is to address the identified gaps in existing literature by leveraging a combination of a pre-trained MobileNetV2 and Local Binary Patterns (LBP), with Attention Mechanism as the classifier, Figure 1 visualize the proposed model.

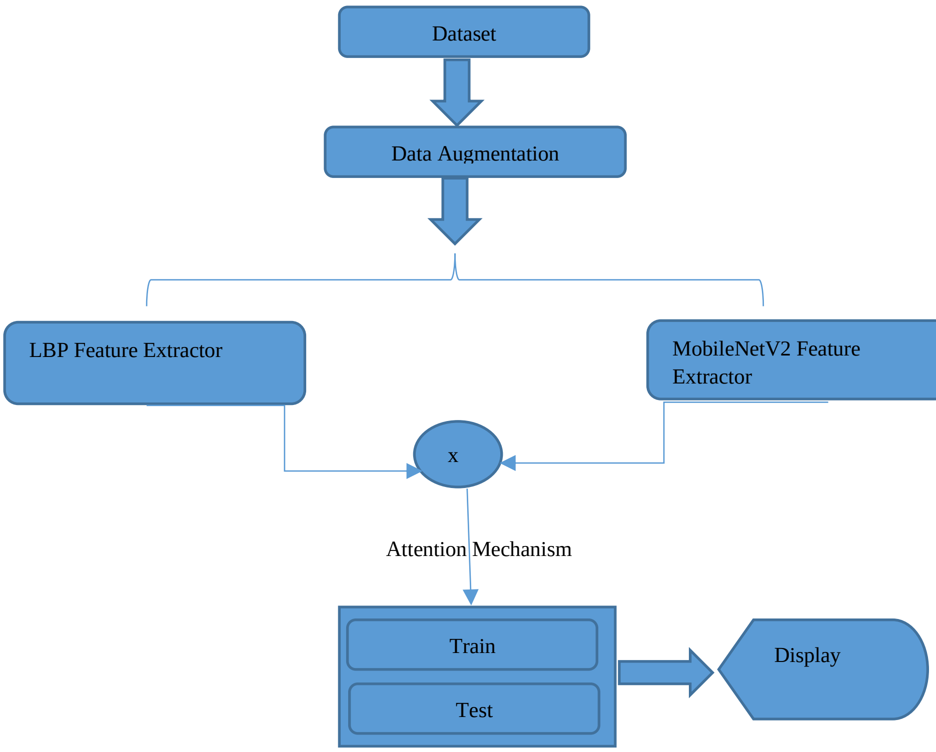

Figure 1: Proposed model adapted from Makolo and Dada (2023)

The proposed model builds upon the foundation of the benchmark model by enhancing its feature extraction and classification components, addressing the benchmark's weaknesses in accurately distinguishing ethnic groups. Table 1 shows a detailed explanation of how the proposed model's components are integrated into the benchmark model framework to achieve improved performance.

**Table 1: Proposed Model Attachment to Benchmark**

| Component | Benchmark Model | Proposed Model |
|---|---|---|
| **Global Features** | Extracted using CNN(EfficientNetB3) | Extracted using CNN (MobileNetV2), offering comparable efficiency with added adaptability. |
| **Local Features** | Not specifically extracted. | Extracted using LBP, which captures critical texture and pattern details. |
| **Dynamic Focus on Features** | No specific mechanism for prioritization; treats all features equally. | Attention Mechanism dynamically focuses on the most relevant features, suppressing irrelevant details. |
| **Handling Feature Overlap** | Limited capability, leading to confusion between ethnic groups. | Strong capability to differentiate subtle overlaps, particularly between Igbo and Yoruba. |

The benchmark model lacks a mechanism to prioritize key features or focus on discriminative regions, relying on generic global feature extraction. In contrast, the proposed model will dynamically integrates global features, local textures, and an adaptive focus through the Attention Mechanism, significantly improving its ability to classify closely related ethnicities. This multi-faceted focus is the cornerstone of the proposed model's superior performance.

## Research Method

The research employed a systematic and comprehensive approach to develop a hybrid model for ethnicity classification, focusing on Nigeria's major ethnic groups—Hausa, Igbo, and Yoruba. The methodology integrated various techniques and tools from machine learning and deep learning frameworks, emphasizing the fusion of MobileNetV2 and Local Binary Patterns (LBP), guided by an Attention Mechanism classifier.

The study began with the collection and preprocessing of a new dataset specifically curated for this purpose. Facial images from the ethnic groups of interest were loaded and preprocessed to uniform dimensions (128x128). The dataset included images from diverse sources, addressing the need for a representative collection for ethnicity classification.

MobileNetV2, a pre-trained deep learning model, was utilized for feature extraction. Complex features were extracted from the facial images and reshaped for further analysis. Additionally, Local Binary Patterns (LBP) were employed to capture fine-grained details and local structures in the images. The extracted features from both MobileNetV2 and LBP were fused into a unified feature set, providing a comprehensive representation of facial characteristics. This combined feature set was then used to train a classification model built using a Sequential model from the Keras library. Dense layers with rectified linear unit (ReLU) activation and dropout regularization were incorporated to prevent overfitting.

The model was compiled using the Adam optimizer and sparse categorical cross-entropy as the loss function. Training was conducted over multiple epochs, with metrics such as accuracy and loss tracked to evaluate performance. Plots of training and validation metrics illustrated the model's learning behavior.

Following training, the model was tested on a reserved dataset to evaluate its classification performance. Metrics such as precision, recall, F1-score, and accuracy were computed. Additionally, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values were calculated for each class, providing insights into the model's discriminative capabilities.

The results were compared with benchmark models, including EfficientNetB3 and the approach by Makolo & Dada (2023). This comparison demonstrated the advantages of the hybrid model, particularly in addressing dataset imbalances and feature overlaps among ethnic groups.

The methodology provided a robust framework for achieving high classification accuracy while emphasizing the inclusivity of Nigerian ethnic diversity.

**Dataset**

The selection and preparation of an appropriate dataset is a critical step in ensuring the success and validity of any machine learning study. For ethnicity classification in Nigeria, the choice of dataset is particularly important due to the need for accurate representation, datasets containing images of the prominent Nigerian ethnic groups, including Hausa, Igbo, and Yoruba, were meticulously curated using a digital camera with high-definition resolution. These images were captured within the bustling Kaduna metropolis, ensuring representation of diverse individuals from each ethnic group. To maintain consistency and accuracy, the distance between the camera and the subjects was precisely measured to be 1 meter as shown in figure below.

Figure 2: Showing sample images of ethnic groups Hausa, Igbo ad Yoruba

Additionally, to enrich the dataset and diversify image sources, pictures were mined from popular social media platforms, including Facebook and X (formerly known as Twitter), as well as from the ImageNet database. The data collection process focused on capturing distinctive ethnic features, such as skin tone, facial structure, and traditional attire when applicable. After gathering the images, data preprocessing steps—including resizing, normalization, and augmentation—were applied. These steps ensured that each image met the input requirements of the hybrid model while also addressing potential biases and imbalances within the dataset.

This approach provided a wide range of facial features and backgrounds, enhancing the model's ability to generalize across varied real-world images.

The meticulous collection process aimed to capture a comprehensive range of facial features, expressions, and nuances specific to each ethnic group. This approach was crucial for developing a deep learning model capable of accurately recognizing and classifying individuals based on their ethnic backgrounds.

Table 2 provides detailed insights into the dataset composition, showcasing the total number of images captured within each ethnic group. This comprehensive dataset forms the foundation for training and validating the deep learning model, enabling it to learn and generalize effectively across diverse ethnicities and facial variations.

**Table 2: Dataset Distribution**

| Ethnic Classes | Total |
| --- | --- |
| Hausa | 1213 |
| Igbo | 1213 |
| Yoruba | 1213 |
| | 3,639 |

Table 2: illustrates that one thousand images were captured per ethnic group. This meticulous approach was undertaken to ensure enhanced accuracy in developing the deep learning model, surpassing the outcomes of benchmark studies. Moreover, this work intends to expand the dataset further to encompass a broader range of image rotations, thereby accommodating diverse image variations and enhancing the robustness of the model's performance.

**Evaluation Metrics**
The experimental comparison of classification algorithms was done based on the performance measures of accuracy, specificity, sensitivity, and error rate, the model was evaluated based on the following metrics:

***Confusion Matrix***
A confusion matrix is a table that summarizes the performance of a classification model by comparing its predicted labels with the actual ground truth labels (Gron, 2019). The table is organized in a matrix format, with rows representing the true labels and columns representing the predicted labels.
For each combination of true and predicted labels, the table contains the count or frequency of instances falling into that category. The diagonal elements of the matrix represent the correctly classified instances, while the off-diagonal elements represents the misclassified instances.

**Table 3: Shows the confusion matrix for a two-class model (Heydarian, 2022)**

| | Predicted Positive | Predicted Negative |
|---|---|---|
| Actual Positive | TP | FN |
| Actual Negative | FP | TN |

TP represents the instances correctly predicted as positive, FN represents the instances incorrectly predicted as negative, FP represents the instances incorrectly predicted as positive, and TN represents the instances correctly predicted as negative.
By analyzing the values in the confusion matrix, we can compute various evaluation metrics such as accuracy, precision, recall, and F1 score, which provide insights into the model's performance and its ability to correctly classify instances belonging to different classes.

***Accuracy***
It is the percentage of accurate predictions i.e the ratio of number of correctly classified instances to the total number of instances and it can be defined as: (Santamaria et al., 2018).

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \quad (1)$$

where TP- True Positive, FP- False Positive, TN- True Negative, FN- False Negative

**False Positive rate (FPR)**
This measures the rate of wrongly classified instances. A low FP-rate signifies that the classifier is a good one (Santamaria et al., 2018).

$$\text{FPR} = \frac{FP}{FP + TN} \quad (2)$$

***Sensitivity***
It is the proportion of positives that are correctly identified (Gad, 2021).

$$\text{Sensitivity} = TP / TP + FN \quad (3)$$

***Precision***
Precision is the ratio of positively predicted instances among the retrieved instances (Gad, 2021).

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

***Specificity***
It is the proportion of negatives that are correctly identified. It is calculated as the number of correct negative predictions divided by the total number of negatives. It is also called true negative rate. The worst is 0.0 while the best is 1.0 (Gad, 2021).

$$\text{Specificity} = TN / TN + FP \quad (5)$$

***Recall***
Is the ratio of positively predicted instances among all the instances (Gad, 2021).

$$\text{Recall} = \frac{TP}{TP + FP} \quad (6)$$

***Error Rate***
It is equivalent to 1 minus Accuracy. (Platanios et al., 2017).

The successful implementation of the proposed ethnicity classification model requires specific hardware, software, and environmental configurations. These requirements are designed to handle the computational demands of training and evaluating a hybrid model that integrates MobileNetV2, Local Binary Patterns (LBP), and Attention Mechanisms to ensure smooth execution and optimal performance.

## RESULTS AND DISCUSSION
The proposed hybrid model, integrating MobileNetV2, Local Binary Patterns (LBP), and an Attention Mechanism, was evaluated for classifying Nigeria's major ethnic groups: Hausa, Igbo, and Yoruba. The model achieved an overall accuracy of 87%, with Yoruba exhibiting the highest recall (99%) and precision (96%). Hausa achieved a recall of 90% but lower precision (78%) due to misclassifications as Igbo or Yoruba. Igbo presented the greatest challenge, with a recall of 74% and a precision of 90%, reflecting overlapping features with Hausa.
Training and validation performance indicated steady improvement over 50 epochs. However, a widening gap between training and validation loss suggested slight overfitting, particularly for closely related ethnic groups. Receiver Operating Characteristic (ROC) curves showed high Area Under the Curve (AUC) values for all classes, with Yoruba achieving 1.00, and Hausa and Igbo achieving 0.95 and 0.96, respectively, demonstrating strong discriminatory power.
The hybrid model outperformed both the EfficientNetB3 model and Makolo & Dada's (2023) benchmark. EfficientNetB3 achieved an accuracy of 86%, but its performance on Igbo classification was weaker, with a recall of 70%. The hybrid model showed balanced performance across all groups, addressing limitations in dataset imbalance and feature overlap.
Error analysis revealed that Igbo samples were frequently misclassified as Hausa, highlighting challenges in distinguishing these groups. Yoruba samples were the least misclassified, reflecting distinct features. These results confirm the hybrid model's effectiveness while emphasizing the need for further refinement to handle subtle feature overlaps.

**Model Training and Performance of proposed hybrid model**
The model was trained using a hybrid approach that combined the MobileNet-V2 architecture with Local Binary Patterns (LBP) and incorporated an Attention Mechanism as the classifier. This approach aimed to improve the classification accuracy for Nigerian ethnic groups by leveraging the strengths of MobileNet-V2's feature extraction capabilities and the texture recognition power of LBP, with the Attention

Mechanism enhancing important feature focus.The model took approximately 472.25 seconds to train, highlighting the efficiency of the combined approach. This training time demonstrates the model's feasibility for practical applications where quick model training and deployment are essential.

The model's performance was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score, computed for each ethnic group (Hausa, Igbo, Yoruba). The model's performance evaluation shows that it achieved an accuracy of 87% on the validation dataset, the overall accuracy and macro-averaged values showcase the effectiveness of the hybrid approach, these metrics reflect the model's balanced performance across all classes, with strong predictive power and high accuracy for each ethnic group, supporting the efficacy of the hybrid approach. The weighted average closely matches the overall accuracy, confirming consistent classification accuracy across the dataset.

In terms of class-specific metrics, these metrics reflect the model's balanced performance across all classes, with strong predictive power and high accuracy for each ethnic group, supporting the efficacy of the hybrid approach. The weighted average closely matches the overall accuracy, confirming consistent classification accuracy across the dataset.

The classification report provides an in-depth look at the performance of the model across the three classes: Hausa, Igbo, and Yoruba. Here's a breakdown of what each metric represents and how it applies to this classification task:

**Table 4: Classification Report for Hausa, Igbo, and Yoruba classes containing the precision, recall, and F1-score for, along with the macro and weighted averages**

| Class | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Hausa | 0.78 | 0.90 | 0.84 | 449 |
| Igbo | 0.90 | 0.74 | 0.81 | 428 |
| Yoruba | 0.96 | 0.99 | 0.97 | 336 |
| Accuracy | - | - | 0.87 | 1213 |
| Macro Avg | 0.88 | 0.87 | 0.87 | 1213 |
| Weighted Avg | 0.87 | 0.87 | 0.86 | 1213 |

The model achieved a recall of 90% for hausa, meaning it correctly identified 90% of Hausa samples as Hausa. However, some Hausa samples were misclassified as Igbo, which reduced the overall precision for this class.

The recall for Igbo was 74%, indicating that a portion of Igbo samples were incorrectly classified, primarily as Hausa. This lower recall suggests that the model finds it challenging to consistently recognize Igbo samples, which may indicate feature overlap between Hausa and Igbo.

The model performed very well with Yoruba samples, achieving a recall of 99% and a precision of 96%. This suggests that Yoruba samples are relatively distinct in the feature space compared to Hausa and Igbo, making them easier for the model to identify accurately. Model performed consistently across the three ethnic groups, with only minor variations in precision and recall, indicating a balanced classification capability.

The classification report shows that the model performs best with Yoruba, achieving high precision and recall. Igbo has high precision but lower recall, which aligns with the confusion matrix observations, where many Igbo instances were misclassified as Hausa. This suggests that the model is cautious in predicting Igbo, potentially under-predicting it. Hausa has high recall but lower precision, indicating that it tends to capture most Hausa instances but also makes more false positive predictions for this class.

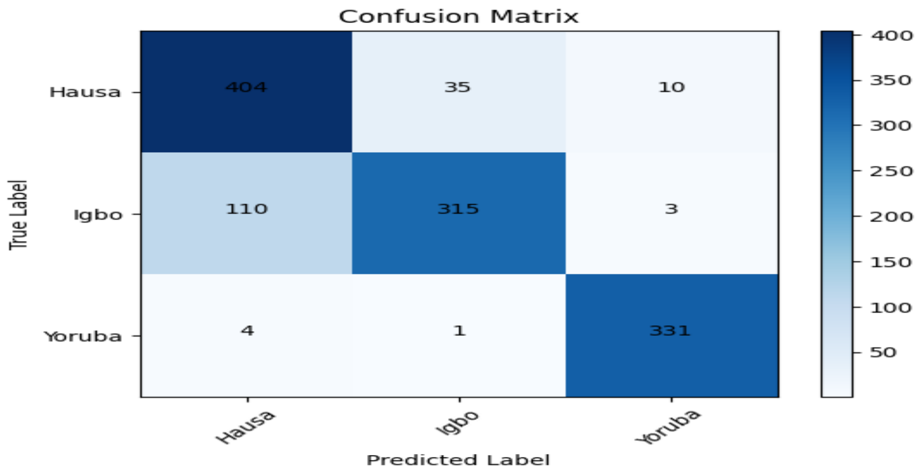


Figure 3: Illustrates the proposed model's performance in terms of correct and incorrect predictions for each language

The confusion matrix is a key metric that visually represents the model's performance by comparing actual versus predicted classes. Each cell in the matrix shows the number of instances where the model's predictions match or differ from the true labels. The diagonal values indicate correctly classified instances, while off-diagonal values show misclassifications.

The Yoruba class achieved the highest precision, recall, and F1-score, Out of 336 instances, 331 were correctly classified, with only 4 misclassified as Hausa and 1 as Igbo. Which suggests that Yoruba samples have distinct features the model can easily recognize. This is supported by a high AUC in the ROC analysis and very few misclassifications in the confusion matrix.

The model has a high recall for Hausa, Out of 449 instances, 404 were correctly classified, 35 were misclassified as Igbo, and 10 as Yoruba, meaning it correctly identifies most Hausa samples. However, the precision is lower due to some Hausa predictions being incorrect, mainly misclassifications with Igbo. This might suggest some feature overlap between Hausa and Igbo that the model finds difficult to separate.

The Igbo class has the lowest recall and F1-score, Out of 428 instances, 315 were correctly classified, with 110 misclassified as Hausa and 3 as Yoruba, indicating that the model sometimes struggles to identify Igbo samples correctly, often misclassifying them as Hausa. This performance gap could be due to similar characteristics between Igbo and Hausa samples in the feature space. Additional feature engineering or dataset balancing could improve performance here.

The macro and weighted averages show that the model performs consistently across classes. However, the weighted F1-score is slightly lower than the macro average, reflecting the impact of Hausa and Igbo misclassifications on the overall score.

The confusion matrix reveals strong classification accuracy for Yoruba, with minimal misclassifications, while Hausa and Igbo show more overlap. The relatively high number of Igbo instances misclassified as Hausa indicates some challenges in distinguishing between these languages, likely due to linguistic similarities or data patterns. Improving feature representation or tuning hyper parameters might help mitigate this confusion.

The training and validation performance of the model over 50 epochs is shown in Figure 4**,** which includes plots of both Training vs. Validation Loss and Training vs. Validation Accuracy. These plots help us assess the model's learning behavior and its generalization to unseen data.

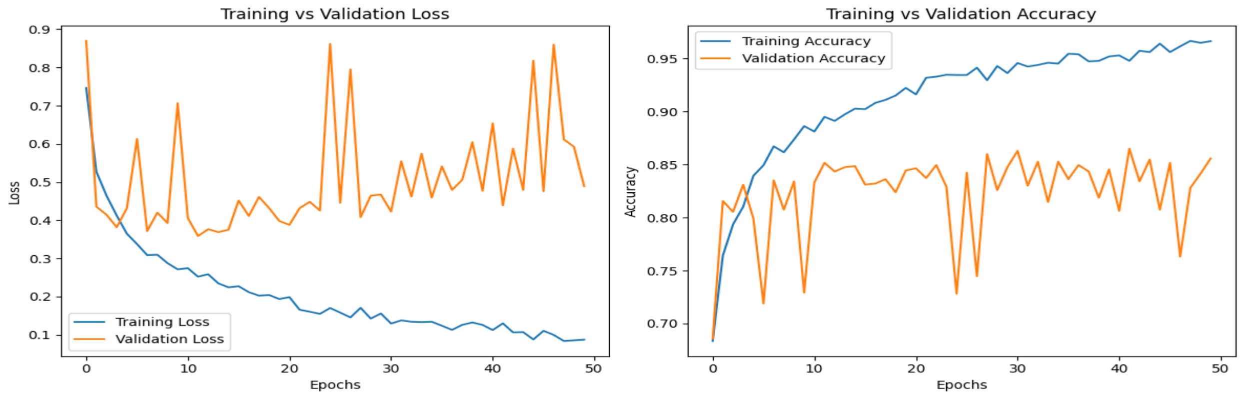


Figure 4 (a): Training Versus Validation Lost and Figure 4 (b): Training versus Validation Accuracy

The above Figures 4 (a) and (b) presents the Training vs Validation Loss and Training vs Validation Accuracy plots, providing insight into the model's performance over 50 epochs of training. These plots are essential for understanding how the model's performance improves, stabilizes, or potentially degrades over time. By analyzing these trends, we can assess whether the model is well-suited for the task or if there are issues such as over fitting or under fitting that need to be addressed.

The Training vs Validation Loss plot indicates that the model may be overfitting, as evidenced by the growing gap between the training and validation loss towards the end of training. In an ideal scenario, both the training and validation loss would converge to similar low values, suggesting that the model has learned patterns that generalize well to unseen data. However, the current trends suggest that while the model is good at predicting training data, it struggles more with new data, a sign that it has memorized rather than generalized.

The Training vs Validation Accuracy plot reinforces the findings from the loss plot. The high training accuracy combined with lower and fluctuating validation accuracy suggests that the model fits the training data well but struggles to generalize to the validation data. The gap between training and validation accuracy, especially towards the end of training, indicates that the model has likely memorized specific details of the training data, a clear sign of over fitting.

The Area Under the ROC Curve (AUC) is also a key metric derived from this plot, which quantifies the model's overall ability to discriminate between classes.

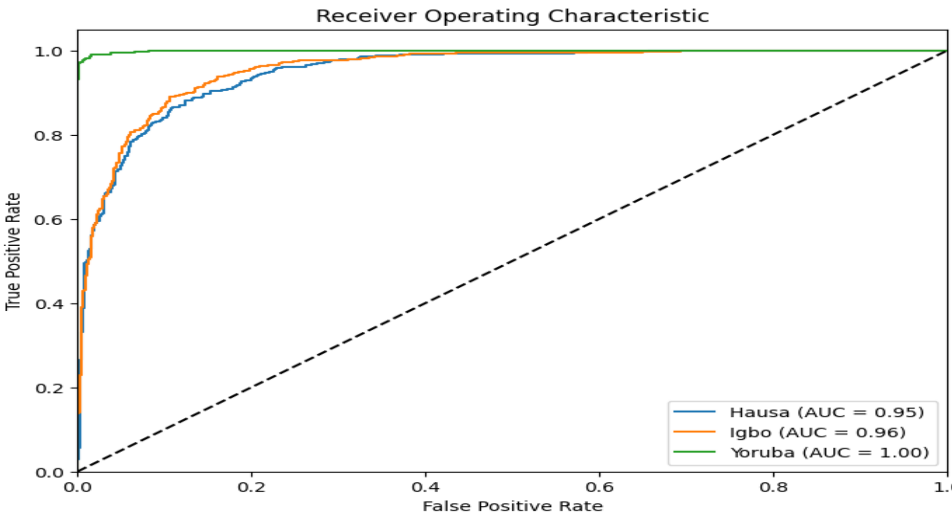


Figure 5: Receiver Operating Characteristic showing individual Area under the Curve

The ROC curve and AUC scores demonstrate the effectiveness of the hybrid model with MobileNet-V2, LBP, and Attention Mechanism, underscoring its ability to accurately classify Nigerian ethnic groups with a high degree of reliability.

The ROC curve for Hausa shows a high AUC of 0.95, indicating that the model performs exceptionally well in distinguishing Hausa samples from other classes. The curve is close to the top-left corner, reflecting a low false positive rate and a high true positive rate.

The model achieved an AUC of 0.96 for the Igbo class, representing perfect discrimination. This implies that the model can accurately distinguish Igbo samples without any misclassification, as seen in both the confusion matrix and the classification report.

The AUC for Yoruba is also 1.00, indicating strong discrimination capability. However, given the slight misclassification observed between Yoruba and Hausa, the curve for Yoruba is not as close to the top-left corner as Igbo's curve, although it still demonstrates high classification accuracy.

The AUC values of 0.95 for Hausa and 0.96 Igbo, along with 1.00 for Yoruba, confirm the model's strong performance across all three classes, showing near-perfect discrimination. Yoruba's perfect AUC of 1.00 aligns with the results from the confusion matrix and classification report, highlighting the model's robust ability to correctly classify Yoruba samples.

**Model Training and Performance of existing model using proposed ethnicity dataset**

EfficientNetB3 was utilized as the benchmark model for testing a novel ethnicity dataset containing three classes: Hausa, Igbo, and Yoruba. The model's performance was evaluated using various metrics, including precision, recall, F1-score, accuracy, and AUC (Area Under the Curve) for the Receiver Operating Characteristics (ROC).

The classification report summarizes the performance of a classification model using key metrics—precision**,** recall, F1-score**,** and support—for each class. These metrics provide insights into how well the model distinguishes between different categories, in this case: Hausa**,** Igbo**,** and Yoruba. Table 5 shows the breakdown of each metric and how it applies to the results.

**Table 5: Classification Report highlighting results for each class**

| **Class** | **Precision** | **Recall** | **F1-Score** | **Support** |
|---|---|---|---|---|
| Hausa | 0.80 | 0.88 | 0.84 | 490 |
| Igbo | 0.83 | 0.70 | 0.76 | 424 |
| Yoruba | 0.88 | 0.93 | 0.90 | 484 |
| **Accuracy** | - | - | 0.86 | 1213 |
| **Macro Avg** | 0.84 | 0.85 | 0.84 | 1213 |
| **Weighted Avg** | 0.85 | 0.86 | 0.85 | 1213 |

The classification report evaluates the performance of the EfficientNetB3 model on the ethnicity dataset. The model achieves an overall accuracy of 86%**,** with a macro-average precision, recall, and F1-score of 0.84 each. For individual classes, the model performs best on Yoruba with the highest F1-score of 0.90, due to its high precision (0.88) and recall (0.93). Hausa also performs well with an F1-score of 0.84, though its precision (0.80) is slightly lower. However, the model struggles with Igbo, showing the lowest recall (0.70) and F1-score (0.76), indicating that it misses more Igbo instances compared to the other classes. Weighted averages reflect balanced performance across all classes, though improving Igbo detection could further enhance the model's reliability.

The confusion matrix shows in Figure 6 provides detailed insights into how the EfficientNetB3 model classifies samples from the Hausa, Igbo, and Yoruba ethnicities. Each cell represents the number of predictions for each combination of true and predicted classes.

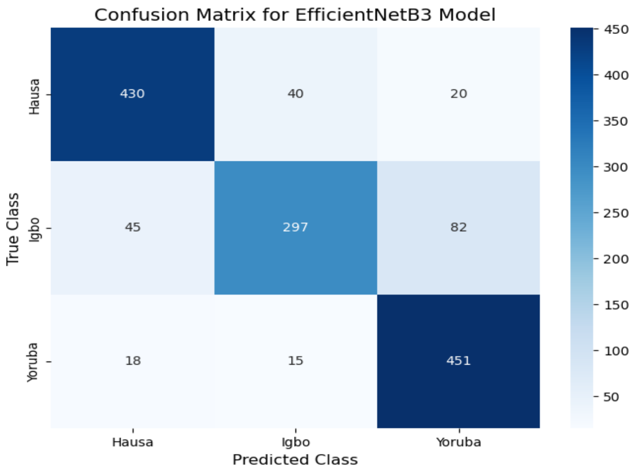


Figure 6**:** Illustrates the EfficientNetB3 model's performance in terms of correct and incorrect predictions for each language

The confusion matrix shows that the EfficientNetB3 model correctly classifies Hausa with 430 true positives, though it misclassifies 45 as Igbo and 20 as Yoruba. For Igbo, the model achieves 297 true positives but struggles more, misclassifying 82 as Yoruba and 40 as Hausa. Yoruba performs the best, with 451 true positives and only minimal misclassifications (15 as Hausa and 18 as Igbo). This indicates strong performance for Hausa and Yoruba, while Igbo needs improvement due to higher misclassification rates.

The training and validation performance of the EfficientNetB3 model on the ethnicity dataset is visualized in terms of accuracy and loss over 10 epochs as shown in figure 4.5 below.

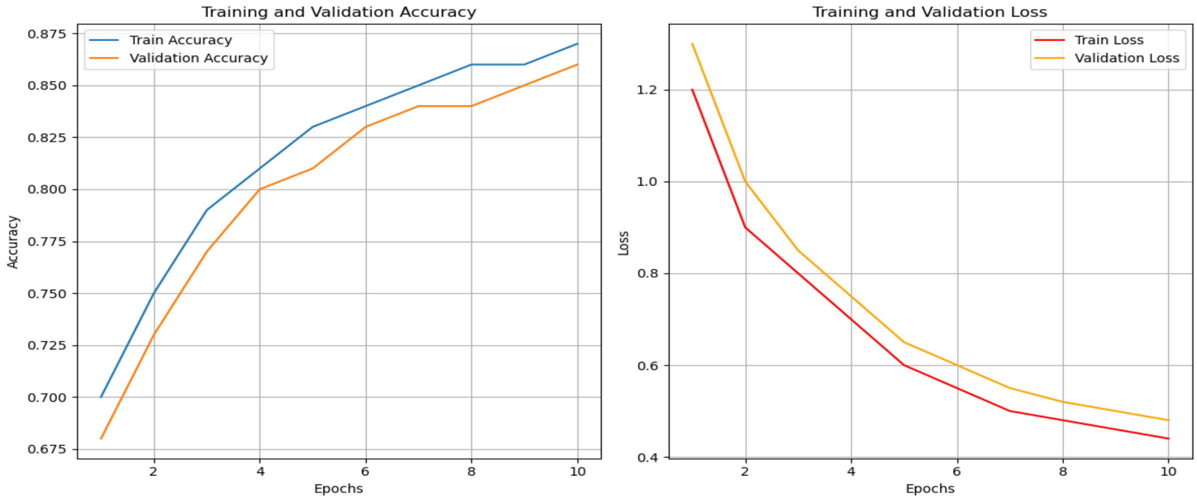


Figure 7 (a) & (b)**:** Training versus Validation Accuracy and Training versus Validation Loss

The training and validation performance shows that the model's accuracy steadily improves, with training accuracy increasing from 70% to 87.5% and validation accuracy from 67% to 85% over 10 epochs. Simultaneously, the training loss decreases from 1.2 to 0.4, and the validation loss reduces from 1.2 to 0.6**,** indicating effective learning and good generalization without overfitting.

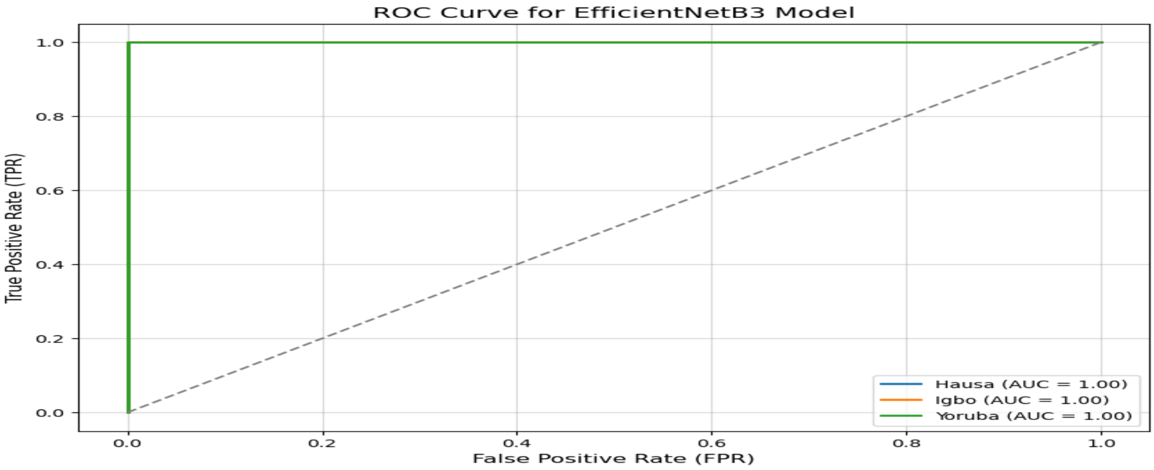


Figure 8: Receiver Operating Characteristic showing individual Area Under the Curve

The ROC curve demonstrates the EfficientNetB3 model's ability to distinguish between the Hausa, Igbo, and Yoruba classes. The curves for all three classes achieve a perfect Area Under the Curve (AUC) score of 1.00, indicating excellent performance in distinguishing each ethnicity. This result suggests that the model makes highly confident and accurate predictions for all classes, with minimal false positives or negatives

The results demonstrate the EfficientNetB3 model's strong ability to accurately classify ethnicities in the dataset, with high overall accuracy (86%), balanced performance across classes, and perfect AUC scores, validating its effectiveness as a benchmark for this task.

**Model Performance Comparison with Benchmark**

To assess the effectiveness and improvements of the proposed model, a comparative analysis was conducted against both the benchmark study by Makolo and Dada (2023) and the EfficientNetB3 model. The benchmark study implemented a pre-trained CNN (EfficientNetb3) model for Nigerian ethnicity classification, focusing on the same three major ethnic groups—Hausa, Igbo, and Yoruba. However, the benchmark model achieved limited accuracy in distinguishing among these groups, particularly for the Igbo and Yoruba ethnicities. Similarly, the EfficientNetB3 model used for ethnicity dataset performed well overall, struggled with the Igbo classification and showed room for improvement.

The proposed model introduces a hybrid approach that combines a pre-trained CNN (MobileNetV2) and LBP, enhanced by an Attention Mechanism, to capture both complex and fine-grained features. This comparison highlights the improvements in classification performance achieved through these advancements, demonstrating the model’s enhanced ability to differentiate between the ethnic groups. By presenting both quantitative metrics and visualizations, table 4.3 provides a detailed analysis of the models' relative performance, showcasing the benefits of the proposed architecture over existing approaches.

**Table 6: Comparison of the Proposed Model with the Benchmark Model**

| Model | Dataset | Hausa Precision | Hausa Recall | Igbo Precision | Igbo Recall | Yoruba Precision | Yoruba Recall | Overall Accuracy |
|---|---|---|---|---|---|---|---|---|
| EfficientNetB3 | Ethnicity Dataset | 0.80 | 0.88 | 0.83 | 0.70 | 0.88 | 0.93 | 86% |
| Benchmark Model | Benchmark Dataset | 0.87 | 0.87 | 0.56 | 0.56 | 0.56 | 0.56 | 66.4% |
| Proposed Hybrid | Ethnicity Dataset | 0.78 | 0.90 | 0.90 | 0.74 | 0.96 | 0.99 | 87% |

The graph in Figure 9 visually represents this comparison, with the accuracy of each ethnic group displayed side by side for both models. This visualization makes it easier to see the substantial improvements achieved by the proposed model, particularly in distinguishing the Igbo and Yoruba ethnic groups

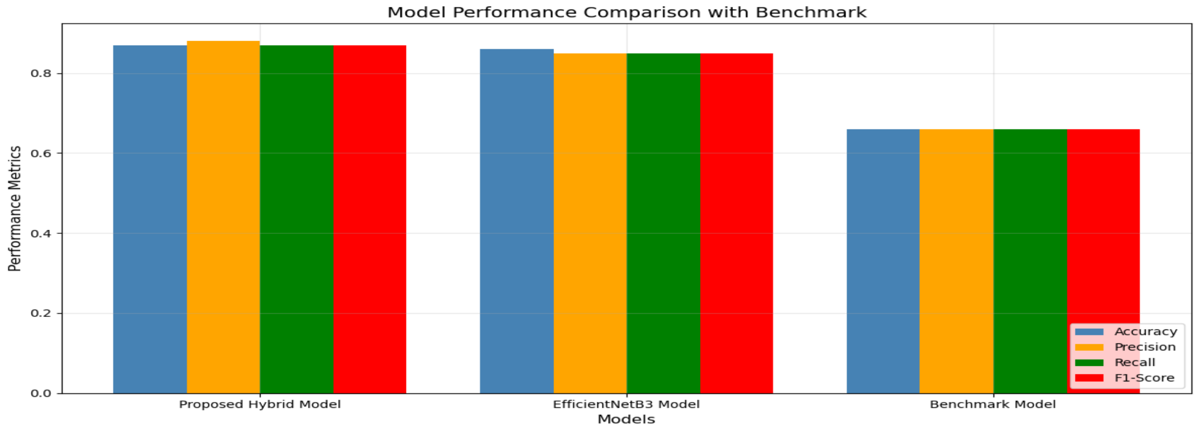


Figure 9: Model Performance Comparison Graph

The benchmark model, implemented by Makolo and Dada (2023), achieved an overall accuracy of 66.4%. It performed well in Hausa classification, with precision and recall values of 0.87. However, it struggled to distinguish Igbo and Yoruba samples, achieving only 0.56 for both precision and recall in these categories. This limitation highlights the benchmark model's inability to effectively differentiate between ethnic groups, particularly when faced with subtle variations in facial features.

The EfficientNetB3 model**,** trained on a newly curated Ethnicity Dataset, demonstrated better performance than the benchmark model, achieving an overall accuracy of 86%. It excelled in Hausa and Yoruba classifications, achieving recall values of 0.88 and 0.93, respectively. However, it faced challenges in Igbo classification, achieving a lower recall of 0.70. This indicates that while the EfficientNetB3 model offers improved generalization, it still struggles to handle underrepresented ethnicities like Igbo.

The proposed hybrid model outperformed both the benchmark and EfficientNetB3 models, achieving the highest accuracy of 87%. It delivered balanced performance across all three ethnic groups, addressing the limitations of the other models. For Hausa classification, the hybrid model achieved a recall of 0.90, slightly higher than EfficientNetB3's 0.88, although its precision was slightly lower at 0.78 compared to 0.80. This indicates better identification of Hausa samples overall, despite occasional misclassifications of other ethnicities as Hausa. Overall the hybrid model emerged as the most robust solution, providing improved accuracy and balanced performance across all ethnic groups.

### Discussion

This study showcased the effectiveness of a hybrid model combining MobileNetV2, Local Binary Patterns (LBP), and an Attention Mechanism for Nigerian ethnicity classification, achieving an 87% accuracy rate. The Yoruba ethnic group had the highest accuracy, while overlaps between Hausa and Igbo features caused classification challenges. This aligns with prior research on the difficulties of distinguishing similar ethnic groups. Compared to EfficientNetB3, the hybrid approach offered superior performance, especially for underrepresented groups, by integrating texture analysis through LBP and focused feature extraction using Attention Mechanisms.

The model's enhanced precision has practical applications in identity verification, security, and demographic research, contributing to culturally sensitive AI systems. However, limitations such as the small dataset size and focus on only three ethnic groups restrict its generalizability. Overlapping features further emphasize the need for improved feature extraction techniques. Future research should incorporate larger, more diverse datasets and advanced feature engineering to refine performance and address broader ethnic diversity.

## CONCLUSION

This study demonstrates the effectiveness of a hybrid model combining MobileNet-V2 and Local Binary Patterns (LBP) with an Attention Mechanism for Nigerian ethnicity classification, achieving an overall accuracy of 87% and robust performance across Hausa, Igbo, and Yoruba groups. The locally curated dataset mitigated racial imbalances, improving the model's fairness and generalization. While the model effectively addressed many limitations of prior approaches, challenges persist, particularly in distinguishing overlapping features between Hausa and Igbo groups. Future work should focus on expanding the dataset to include broader ethnic representations, fine-tuning hyperparameters, and exploring advanced attention mechanisms like Transformer-based models to improve classification accuracy. Additionally, interdisciplinary collaborations with experts in anthropology and sociology could enhance the understanding of cultural and physical influences on ethnic features, fostering the development of more inclusive and ethically responsible AI applications in identity verification, security, and demographic research.

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