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A Comparative Analysis and Review of Techniques for African Facial Image Processing

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Abstract: Facial recognition algorithms require diverse datasets to perform well across various applications. However, the scarcity of comprehensive African facial image databases hinders the accuracy of models for the African population. This paper assesses the potential of available facial image collections for facial recognition in Africa. We evaluate the efficiency of PCA and SVM in capturing and classifying facial features among three African ethnic groups, leveraging their ability to enable accurate and reliable facial recognition despite varying conditions. Our approach involves collecting and evaluating indigenous African datasets based on temporal relevance, geographical coverage, and demographic representation while considering ethical and cultural issues in data collection. Our results demonstrate that PCA captures facial variations, and SVM achieves an accuracy rate of 55% with notable group differences. These findings highlight the importance of culturally sensitive approaches and representative datasets in ensuring fairness and reliability in facial recognition systems. Future work will focus on expanding data collection to underrepresented regions and fostering collaborations between researchers and local communities to develop inclusive and equitable facial recognition technologies.

Keywords: Digital Signal Processing, Facial Image Processing, Bias, Geo-diversity, Facial Image Datasets, Machine Learning, Classification and Clustering

1. INTRODUCTION

Facial recognition systems have significantly enhanced security and efficiency in controlled environments, such as airports, government buildings, and financial institutions, by providing rapid and accurate identification capabilities [1]. Nevertheless, adapting to real-life situations, particularly within Africa's diverse and distinctive environment, poses a significant obstacle. The inclusivity and accuracy of facial recognition systems heavily rely on the representation and variety of facial image datasets. This need is even more pronounced in Africa, where the unique qualities and variations within the population necessitate the development of customized datasets [2].

The importance of diversity and inclusion in Facial Recognition Technology (FRT) cannot be overstated [3]. The effectiveness of these systems hinges on their ability to recognize and categorize faces across different races, facial features, and skin tones. However, many existing facial recognition algorithms, often trained on datasets biased towards non-African populations, struggle to produce accurate and reliable results for African faces. This bias results in higher error rates and limits the effectiveness of these systems in African contexts[4].

Facial recognition technology has gained prominence in recent years, with applications ranging from security to technological advancements [5]. However, a significant research gap exists in the African context, where a scarcity of publicly available, diverse, and representative facial image databases hampers the development of robust facial recognition algorithms. This shortage disproportionately affects African populations, whose distinct facial features are underrepresented, leading to reduced accuracy and inclusivity in facial recognition systems. As a result, the technology's potential benefits are limited, and its deployment across the continent is hindered by a lack of culturally responsive solutions [2].

Addressing this gap is crucial for several reasons. First, many facial recognition systems are predominantly trained on datasets that over-represent Caucasian faces,[6] leading to higher error rates when applied to African populations. This bias not only reduces the effectiveness of the technology but also raises significant ethical concerns regarding fairness and equity in technological applications [7]. Ensuring equitable performance across all racial groups

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is essential for fostering trust and acceptance of facial recognition technologies.

Moreover, reliable facial recognition systems are critical for law enforcement and security purposes, such as identifying individuals in surveillance footage and verifying identities at security checkpoints [8]. Improving the accuracy of these systems for African populations helps prevent wrongful accusations and detentions, ensuring justice and fairness in legal contexts. In healthcare, facial recognition can assist in patient identification, monitoring, and personalized care, ensuring that patients from African populations receive accurate and consistent treatment [9]. The development of unbiased facial recognition models aligns with the broader goals of ethical AI, promoting fairness, accountability, and transparency in technology. By focusing on historically underrepresented populations, we can address and correct longstanding inequities in technological development. Improved datasets and models can inform global standards and policies for facial recognition technologies, ensuring they are fair and just for all populations. Promoting research and development in diverse datasets encourages international collaboration, fostering innovation and best practices across borders [5].

Designing accurate and representative facial recognition models for African populations has far-reaching implications across various sectors. An accurate system will improve the identification of individuals from surveillance footage, reduce the risk of mistaken accusations in law enforcement, and facilitate fair and personalized treatment in healthcare. [3]. Beyond these applications, advancements in facial recognition technology in Africa contribute to broader societal objectives of promoting technological inclusivity and redressing past biases [10].

This paper aims to address a critical research gap by conducting a comprehensive comparative analysis of African facial image datasets. We survey the existing landscape of African facial image datasets, discuss the challenges in dataset collection, and propose strategies for developing inclusive datasets that best represent the diversity of African populations. Culturally sensitive approaches and collaborative partnerships with local communities will be emphasized as foundational for advancing facial recognition technology in Africa.

The current research project seeks to further the development of facial recognition systems through effective dialogue and collaboration among researchers, policymakers, and communities. This collaboration will influence ethical considerations and shape societal acceptance of such technologies in African contexts. The objective of developing inclusive and reliable models for facial recognition in Africa aligns with a global imperative: ensuring that technological advancement benefits all of humanity.

This paper has three main contributions. First, it presents a comprehensive analysis of the current state of African facial image collections, highlighting their features and demographic representation. Secondly, It examines cultural nuances and privacy concerns while exploring the challenges in gathering facial image datasets in the African context, with a focus on inclusive and diverse datasets. Last, but not least, It lays the groundwork for future efforts in creating inclusive datasets, offering solutions to current challenges, and advancing facial recognition technology in Africa. This research sought to contribute to the processes of building fair and accurate facial recognition systems that consider the distinctive characteristics of the African continent.

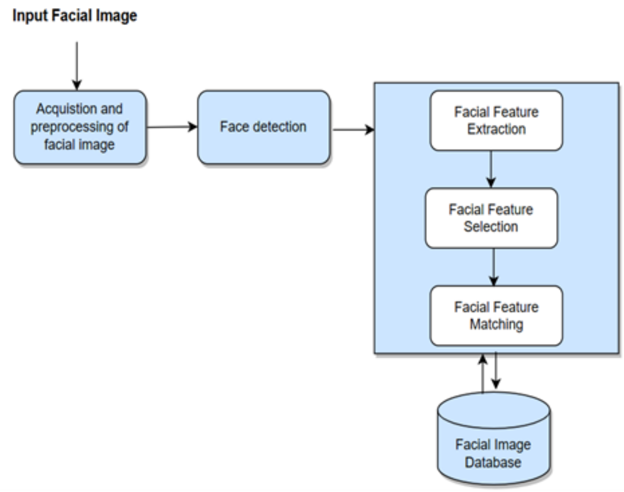

Figure 1. Overview of facial recognition systems and facial image database

The paper is structured as follows: Section II covers the Literature Review. Section III details the methodology employed for compiling African datasets, analyzing dataset characteristics, and examining environmental factors. Section IV presents the results and analysis. Section V discusses the conclusions drawn from the study. Section VI outlines future directions for dataset creation and collection.

2. RELATED WORKS

A. *Overview of Facial Recognition Systems*

There have been a great number of activities in the field of human facial recognition research worldwide. Its extraordinary success and wide range of social applications have drawn substantial attention from several areas, including computer vision, machine learning, and artificial intelligence, especially in the past five years [11] [12]. Any face recognition system's main objective is to identify a human from static facial images in photos, video data, data streams, and context information about the active use of various data components. Figure 1 outlines the basic overview of a facial recognition system and describes how the facial image dataset serves as the core to the feature extraction, feature selection, and feature matching of the facial recognition system.

The facial images in the database determine the performance of the facial recognition systems, most especially in carefully regulated settings with uniform illumination, low occlusion, and conventional stances, facial recognition systems have shown impressive performance [20]. Current facial recognition methods work well for identification and verification in these regulated environments. Due to these achievements, the area has advanced and has seen broad applications in several fields, including access control, security, and law enforcement.

While face recognition systems have demonstrated dependability in controlled environments, their success is limited by the inherent constraints of these settings. Controlled environments provide a stable and regulated background, optimizing facial recognition algorithm performance. However, it's crucial to acknowledge the limitations of these successes when applied to real-world scenarios. Unlike controlled contexts, real-world situations present complex and dynamic environments that cannot be fully replicated in controlled settings. In unrestricted surroundings, various obstacles arise, including diverse lighting conditions, a wide range of facial expressions, and occlusions [13]. These factors significantly impede the efficacy of face recognition technology in practical applications, characterized by uncertain and dynamic environments

Within this framework, the limitations of facial recognition systems are exposed in the context of African environments. The diverse and dynamic nature of African surroundings underscores the need for facial recognition technology to transcend the constraints of real-world complexity. To ensure accurate and reliable performance in a variety of unpredictable environments, facial recognition technology must evolve to address the unique challenges posed by African contexts. This includes adapting to diverse lighting conditions, accommodating varied facial features and expressions, and mitigating the impact of occlusions. By acknowledging and addressing these challenges, facial recognition technology can become more robust, inclusive, and effective in African environments [14].

B. Existing Datasets for Facial Recognition

1) Overview of Global Datasets: An analysis of the datasets used to train and assess these systems is necessary to have a thorough grasp of facial recognition's performance in real-world situations [15]. By offering standards for algorithmic performance, a variety of datasets have contributed significantly to the global advancement of facial recognition technology. The effectiveness that has been noted in controlled circumstances can be attributed to the fact that these datasets frequently include a variety of facial photos. One important research difficulty is evaluating the performance of face recognition systems, which has led to the creation of multiple face recognition standards [16]. These benchmarks are essential resources for assessing recently suggested algorithms

2) Limited African-Specific Dataset: There is, nevertheless, a significant void in these datasets' depictions of African faces. African-focused datasets are noticeably scarce, which makes it difficult to create facial recognition algorithms that are customized to the distinctive features of African populations. There is an urgent need for datasets that more accurately depict the richness and diversity of African faces because the current representation is inadequate for accurately recognizing and verifying individuals with varied ethnic backgrounds and facial traits [10].

Racial Faces in-the-Wild (RFW) Dataset: Racial Faces in-the-Wild (RFW) Dataset was Introduced by [17], the RFW dataset is designed to evaluate the racial biases of facial recognition algorithms. It contains images from four racial groups: Caucasians, Asians, Indians, and Africans. Their analysis showed that most state-of-the-art algorithms performed worse on African and Indian subsets compared to Caucasian and Asian subsets, highlighting the need for more balanced datasets.

Balanced Faces in-the-Wild (BFW) Dataset: To tackle the issue of demographic bias in facial recognition, [18] developed the Balanced Faces in the Wild (BFW) dataset, a meticulously curated collection of images that ensures equal representation across various demographic groups. By providing a balanced dataset, we aim to enhance the fairness and accuracy of facial recognition models, ultimately reducing disparities in performance across different populations. The BFW dataset has already been instrumental in benchmarking and refining facial recognition systems, paving the way for more inclusive and equitable outcomes in real-world application.

Diversity in Faces (DiF) Dataset: The DiF dataset provides a large and diverse set of facial images annotated with various attributes, including age, gender, and skin tone. This dataset has been instrumental in studying and mitigating biases in facial recognition systems. DiF has enabled researchers to explore the effects of demographic diversity on the performance of facial recognition algorithms and to develop techniques to reduce bias.

3)Biases in Current Datasets: Furthermore, the problems faced by facial recognition systems are exacerbated by biases present in current datasets. These biases can cause skewed performance, with some groups seeing higher accuracy rates than others [19]. They frequently reflect the demographics of the people who created the datasets or of the prevailing communities.

[20] highlighted significant biases in commercial FRT systems, showing that error rates for darker-skinned individuals, particularly women, were substantially higher than for lighter-skinned individuals. The study underscored the need for more diverse datasets and fairer algorithms. This study sparked widespread awareness and led to increased scrutiny and regulatory discussions regarding the ethical use of facial recognition technology.

[21] This study analyzed the performance of several state-of-the-art facial recognition systems and found consistent biases across different skin tones and gender groups. The researchers called for the development of algorithms that perform equitably across all demographics.

[20] This comprehensive review of fairness in biometric systems highlighted the challenges and progress in creating unbiased facial recognition technologies. The review emphasized the importance of diverse training data and the need for continuous assessment and mitigation of biases.

C. Overview of African Indigenous Datasets

African Indigenous Datasets are collections of data that relate to the diverse and rich cultures, languages, histories, and traditions of the indigenous peoples of Africa. These datasets can be used for various purposes, such as research, education, preservation, and innovation. The most widely used facial image databases that are publicly available in the development of facial image processing applications have been reviewed by [22]. However, here is a review of the African facial image dataset. *1) South African Adult Male Dataset:* The purpose of the study by [23] was to create a dataset on how the faces of African men from South Africa age. They wanted to collect data on how aging affects the African population. They took pictures of 189 black South African men who were 20 years old or older, using a Canon EOS 1300D camera and an 18- to 55-mm EFS lens. They made sure the men were in the same positions. They had 30 men for each age group, except for the 80+ group which only had 9 men. They used a system to score facial aging, based on earlier research, to measure age changes that are not related to size or shape, such as wrinkles and sagging near the eyes. The study found that black South Africans and Europeans have some things in common when they age, but also some differences. Most of the things that change with age only go in one direction, but they change at different speeds. Some things do not change much with age, such as how wide the mouth, nose, and ears are, and how long the nose and ears are.

2) CASIA-Face-Africa: [2] developed CASIA-Face-Africa, a large-scale database of African face images. The database has 38,546 images of 1,183 African individuals, taken with multi-spectral cameras under different lighting conditions. The database also records the demographic and facial expression information of the subjects and labels each face image with 68 facial key points for landmark detection. The graphical statistics of this database are shown in Figure 2. The database offers various evaluation protocols for different applications and tasks, based on different scenarios and partitions. This database is a useful resource for researching face biometrics for African individuals, such as face image preprocessing, face feature analysis and matching, facial expression recognition, sex/age estimation, ethnic classification, and face image generation. The database also provides the results of the latest face recognition algorithms without re-training as baselines.

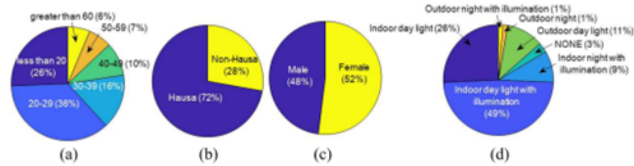

Figure 2. CASIA Graphical statistics of database of age, ethnicity, sex and capturing condition

3) The Ethnicity Aware Training Dataset: Musa created the Ethnicity Aware Training Dataset in 2022 as part of his project to use machine learning to reduce facial recognition bias in Africa. The dataset by [24] was designed to solve the problem of Caucasian faces being more accurately recognized than African and other high-melanin faces by most facial recognition models, which are mostly trained on Caucasian faces. The paper suggests building deep learning models that can detect African tribal marks to enhance facial recognition systems. The Ethnicity Aware Training Dataset has two types of data sources: primary and secondary. The primary data came from photographers and online social platforms, which had the feature attributes of African faces, such as tribal marks. The secondary data came from online African datasets that are publicly accessible, such as Kaggle and Ethnicity Aware Training Datasets. The Ethnicity Aware Training Dataset intends to tackle the issue of bias in facial recognition due to training data selection. It offers four training datasets: BUPT-Balanced Face, BUPT-Globalface, BUPT-Transferface, and MS1M wo RFW. These datasets can help examine facial bias and achieve equitable performance in facial recognition.

4) African Database of High-Resolution: [25] created a high-quality African male database of faces from photos and CCTV videos, which can be used for forensic facial comparison research. The database has 6220 low-quality photos of 622 people in five different angles, and 334 people's CCTV videos taken in real situations. The article explains how the database was made, what it contains, how it is divided, and what it can be used for. The paper also discusses the problems and restrictions they encountered while making the database, especially in getting CCTV videos and following ethical rules for a face database.

5 African Ethnic Faces: The African Ethnic Faces database was used in a research paper titled "Similarities in African Ethnic Faces from the Biometric Recognition Viewpoint by [13]. The paper explores how facial recognition performance metrics are affected by 28 different African ethnicities. By analyzing the genuine and impostor score distributions, the paper examines the impact of inter-ethnic differences on face recognition performance using a database of Nigerian subjects from 28 different ethnicities. The study concludes that while there are significant differences in the Caucasian/Asian set, facial identification performance is not notably influenced by varying African ethnicities.

6 Data-Centric Face Database: [26] Discuss the SmileID face recognition system, which is a commercial system designed for frontal-face identity verification on mobile devices in Africa. The system was developed using the Data-Centric Face database. The authors present a case study on building and deploying a real-world face recognition system that must work primarily on non-Caucasian faces. They emphasize the importance of a data-centric approach, which involves training a state-of-the-art network of African faces. The study shows that such an approach yields strong results and can be more effective than commercial "multi-purpose" systems like AWS Rekognition, especially when dealing with low-power handsets and selfies in frontal-only poses. The SmileID system outperforms Rekognition on a benchmark dataset for frontal authentication, achieving an 11% gain over a baseline Arc-Face implementation by training on an African dataset. Additionally, it improves homogeneity by 16% and completeness by 21%.

7 Yoruba Igbo Hausa (YIH) dataset: [27] developed a Convolutional Neural Network-based Ethnicity Classification Model and created a dataset called the Yoruba Igbo Hausa (YIH) dataset. The dataset consists of 279 images and is used to solve the problem of ethnicity classification using deep convolutional neural networks. The authors propose a new approach and evaluate the method in three scenarios: (i) black and white people classification, (ii) Chinese and Non-Chinese people classification, and (iii) classification of Han, Uyghurs, and Non-Chinese. The proposed models achieve near state-of-the-art performance in age, gender, and race recognition on datasets like UTKFace. Additionally, when used as feature extractors for facial regions in video frames, the models outperform previous state-of-the-art single models for emotion classification on datasets like AFEW and VGAF. The experimental results on both public and self-collected databases show the effectiveness of the proposed method. The trained models and source code are publicly available on GitHub

8 Pilot Parliaments Benchmark (PPB) Dataset: The Pilot Parliaments Benchmark (PPB) Dataset, also known as the PPB dataset, was developed by [28]. The dataset was used to evaluate the accuracy and bias of facial analysis algorithms and datasets about gender and skin type. The authors used the Fitzpatrick Skin Type classification system, which is approved by dermatologists, to determine the distribution of gender and skin type in two facial analysis benchmarks, IJB-A and Adience. They found that these benchmarks were largely made up of lighter-skinned subjects (79.6% for IJB-A and 86.2% for Adience). To solve this issue, they introduced a new facial analysis dataset that is balanced by gender and skin type. The authors evaluated three commercial gender classification systems using their dataset and discovered that darker-skinned females are the most misclassified group, with error rates of up to 34.7%. In contrast, the maximum error rate for lighter-skinned males is only 0.8%. These significant disparities in the accuracy of classifying darker females, lighter females, darker males, and lighter males in gender classification systems are a cause for concern. Commercial companies must address these disparities if they wish to build a genuinely fair, transparent, and accountable facial analysis algorithm.

9 Tanzania dataset: In 2021, Liu and his colleagues created a dataset for Tanzania, which comprises 3555 images [29]. After applying the exclusion criteria, 960 participants were excluded from the analysis, and the remaining 2,595 unrelated participants were kept for the genetic analysis. The main purpose of this dataset was to develop genome scans of facial features in East Africans and to compare them across different populations to reveal new associations. The study aimed to explore the genetic basis of facial characteristics among East African populations. The researchers used an open-ended data-driven phenotyping approach to analyze 2,595 3D facial images of Tanzanian children. The genome scans of these complex shape characteristics showed significant signals at 20 locations. These signals were found to be enriched for active chromatin elements in human cranial neural crest cells and embryonic craniofacial tissue. This indicates that facial variation has an early developmental origin. Furthermore, the study identified 10 association signals that are common to Europeans.

10) Ongoing African database collection project: An ongoing project in Africa involved the collection of a database that was used to create an Empirical Comparative Analysis of Africans and Asians Using DCNN Facial Biometric Models [10]. The paper was presented at the CCBR 2022: Biometric Recognition conference. The study compares the racial biases present in Asians and Africans in various facial biometric tasks. For the study, 251 images were captured using the same camera sensor and under controlled conditions. The authors examined the performances of multiple DCNN-based models on face detection, facial landmark detection, quality assessment, verification, and identification. The results indicated that most algorithms performed better with Asian faces compared to African faces under the same imaging and testing conditions.

D. The Significance of African Facial Image Datasets

The development of facial recognition technology—a technological solution with several applications across a variety of domains begins with the use of facial image datasets. This section examines the vital significance of these datasets within the African setting, examining the benefits and drawbacks of using facial recognition technology. Facial recognition technology adoption and development offer a transformative opportunity with many benefits in Africa. The diverse and fast-expanding population of the continent creates the ideal environment for utilizing facial recognition in critical areas including identity verification, security, personalized services, and human-computer interaction [30]. The following are some core benefits of face recognition technology in Africa;

1) Enhanced Security Measures: Strengthening security measures in high-risk places like airports, borders, and congested public spaces can be greatly aided by facial recognition technology. Strong identity verification systems strengthen the overall security architecture by reducing the risks of identity theft, illegal access, and identity fraud [31].

2) Efficient Identity Management Systems: The technology provides a way around problems with official identity documents. Face recognition emerges as a substitute for official identification credentials in Africa, where a large number of people lack such. Making it easier to obtain necessities like banking, healthcare, and government support, encourages financial inclusion.

3) Improved Customer Experience: In a variety of industries, facial recognition technology has the power to transform customer service and customer experience completely. Businesses may offer individualized services, customized recommendations, and smooth interactions by utilizing facial recognition capabilities. This results in higher levels of client engagement and happiness, especially in the retail sector where it makes targeted marketing and quick payment procedures possible.

4) Support for Law Enforcement: Facial recognition technology can help African law enforcement authorities with surveillance and crime prevention. The technology makes it possible to monitor public areas, identify and trace suspects with efficiency, and reduce criminal activity. This makes a major contribution to both preserving public safety and lowering crime rates.

5 Medical Care and Pandemic Control: In pandemic preparedness and healthcare, facial recognition technology can be quite useful. It can be applied to contactless identification, mask compliance monitoring, and public space health protocol adherence [32]. This extra application improves public health initiatives, particularly in times of health emergencies such as pandemics. Despite several benefits, some obstacles must be overcome before facial recognition technology can be widely used and developed in Africa. The challenges and factors that must be considered for facial recognition technology to be successfully incorporated into various facets of African society are examined in the next subsection.

E. Challenges of Facial Recognition Technology in Africa

Facial recognition technology, while holding immense potential, faces several challenges in the African context that impede its adoption and development. This section breaks down these challenges into key subcategories, addressing issues related to dataset availability, resource constraints, and ethical considerations.

1) Limited Availability and Diversity of Facial Datasets:

- Size and Diversity Constraints: The lack of extensive facial datasets specifically gathered from African populations is one of the main obstacles. The plethora of ethnicities, age groups, gender identities, and environmental conditions prevalent throughout the continent are frequently not well represented in existing statistics due to their lack of scale and diversity. This limitation negatively affects the performance and accuracy of face recognition algorithms, which may lead to biased results and decreased efficacy [2].

- Necessity for Expanded Datasets: African facial databases need to be expanded and diversified to meet this problem. Academia, business, and government agencies must work together to conduct collaborative research projects to gather, manage, and distribute high-quality datasets that accurately reflect the wide range of demographics and traits found in African people. These cooperative methods make use of the resources and experience of several parties to help gather more comprehensive and representative datasets [33].

- *Limitations on Resources:* One major limitation is equipment and funding restrictions. Comprehensive data-gathering activities are significantly hampered by resource constraints. Large-scale facial dataset collection, annotation, and maintenance demand a lot of resources, such as money, supplies, and qualified workers. These resources are few in many African nations, which makes it difficult to collect data at the necessary size.

- Need for Adequate Resources: To overcome this obstacle, sufficient funds and resources must be set aside to assist data collection efforts. Governments, international organizations, and academic institutions working together can offer financial and technical support, giving African researchers the tools; they need to create reliable facial datasets.

2) Ethical Considerations and Privacy

- Creating Ethical Structures: The development and application of facial recognition systems must take privacy and data protection ethics very seriously. Like any other region, Africa has to set moral guidelines and legal restrictions on the gathering, keeping, and application of facial data. Data security, consent, and individual rights should be given top priority in these frameworks.

- Cultural Alignment and Collaboration: Researchers, legislators, and civil society organizations must work together to define ethical standards that respect African cultural values and consider particular sociopolitical circumstances. It is feasible to build confidence, promote wider participation in data-gathering initiatives, and guarantee the proper application of facial recognition technology by considering cultural quirks [34].

3) Unavailability of African Faces in Datasets

- Geographical Bias and Data Collection Limitations: The under representation of African faces in datasets that are accessible to the public is a result of constraints in the earlier data collection efforts, which were frequently focused on certain regions or demographics [10]. The development of inclusive facial recognition systems has been hampered by the poor representation of facial traits caused by this geographic bias.

- Urgent Need for Dedicated Efforts: Given these obstacles, concerted efforts are desperately needed to close the current disparity and deal with the lack of pertinent African faces in facial image collections. To produce datasets that faithfully capture the diversity of African faces entails overcoming constraints on data collecting, honoring cultural and privacy concerns, and cultivating cooperative relationships. The ultimate objective is to aid in the creation of face-recognition systems that are accurate, fair, and applicable worldwide.

- Cultural and Privacy Concerns: The difficulty is compounded by cultural and privacy considerations, given the disparities in traditions and sensitivities throughout the continent. To overcome this, it is necessary to recognize and honor these cultural quirks, cultivate trust, and promote wider involvement in data-gathering activities [35].

- Insufficient Collaboration: Insufficient collaboration between researchers and local communities exacerbates under-representation. Establishing meaningful partnerships with diverse communities is essential for overcoming cultural differences, gaining local insights, and ensuring ethically sound data collection methods.

Table 1 illustrates the summary of the reviewed African facial dataset.

3. METHODOLOGY

A. Dataset Collection

The collection and analysis of African facial image datasets are essential for understanding and addressing racial bias in facial recognition systems. This section provides a detailed explanation of the methods used to collect and analyze these datasets, focusing on sources, selection criteria, and preprocessing steps.

1) Source Publicly Available Databases *CASIA-Face-Africa:* A comprehensive dataset specifically collected for enhancing the representation of African faces in facial recognition research. It includes a diverse range of facial images with detailed annotations as discussed in Section II.

Labeled Faces in the Wild (LFW): This dataset includes a diverse range of facial images, including those of African descent.

Racial Faces in the Wild (RFW): A dataset specifically designed to address racial diversity, containing substantial African facial images. African Face Database (AFDB): A dataset created to enhance the representation of African faces in facial recognition research.

2) Selection Criteria Ensuring the dataset represents a wide range of African ethnic groups. Collecting data from different regions across Africa to account for geographic variability. Selecting high-resolution images with clear facial features, avoiding those with extreme lighting conditions or occlusions. Finally, ensure all images are collected with proper consent and adhere to ethical guidelines.

3) Preprocessing Steps For data preprocessing, a number of steps were done to guarantee consistency in the datasets for appropriate usage in facial recognition and other applications. The preprocessing steps include:

i Normalization of image sizes: Images are standardized with the same size, say 48x48 pixels, to make sure there is uniformity in the dataset. ii. Conversion to grayscale: When not necessarily requiring color information, images were turned into grayscale for the reduction of dimensionality of data and its processing is easy [27].

ii Face alignment using facial landmarks: Facial landmarks were used to align faces to maintain uniformity of pose and orientation. This helps in preserving the integrity of the features of a face and minimizes variations due to facial orientation affecting the process of recognition.

iii Manual Labeling: Some techniques used manual labeling of images with their racial classification to update images for accurate classification and to know the possible biases in the datasets.

B. Compilation of African Datasets

Search Strategies: To compile a comprehensive evaluation list of available African facial image datasets, a systematic approach was employed in the search process using Algorithm 1. We performed extensive searches across scholarly databases, repositories, and relevant platforms to find datasets that specifically focus on African populations. We used keywords like "African facial datasets," "ethnic diversity facial images Africa," and "Indigenous African faces datasets" to ensure that our search process was inclusive.

1) Inclusion Criteria: The inclusion criteria were established to ensure the selection of datasets that align with the objectives of the study. Only datasets featuring facial images of individuals with diverse ethnic backgrounds representative of the African continent were considered. Additionally, datasets were included based on their availability to the general public, ensuring transparency and accessibility for researchers and developers. To formalize

TABLE I. SUMMARY OF THE REVIEWED AFRICAN FACIAL DATASET

S/N	Database Name	Source	Total Images	Number of unique participants	Method of collection	Gender	Age
1	South African Adult Male	[23]	108	30	Web Crawling	M = 100%, F = 0%	20-80
2	CASIA-Face-Africa	[2]	38,546	1,183	NIR Camera system	M = 48%, F = 52%	20-40
3	African Ethnicity Aware Training dataset	[24]	1125	80	CMOS Camera	nil	nil
4	The Database	[25]	6220	622	Camera and video stream	M = 100%, F = 0%	18-35
5	African Ethnic Faces	[13]	551	551	Camera and video stream	M = 65%, F = 35%	nil
6	Data Centric Face	[26]	22,330	nil	Cameras	nil	nil
7	Yoruba Igbo Hausa (YIH) dataset	[27]	279	279	Camera	M = 54%, F = 46%	16-60
8	Pilot Parliaments Benchmark (PPB) Dataset	[28]	661	661	Camera	M = 56%, F = 44%	nil
9	Tanzania dataset	[29]	3,555	3,555	Camera	M = 45%, F = 55%	3-21
10	ongoing African database collection project	[10]	251	251	Camera	M = 52%, F = 48%	20-60

Algorithm 1 Africa Facial Dataset Search

```
Input:
    Keywords = ["African facial datasets," "ethnic diversity facial images Africa," "indigenous African faces datasets"]
    Databases = ["ScholarlyDatabase1", "Repository2", "Platform3"]
Output: AfricanDatasets = []    ▷ Initialize an empty list
for each Keyword in Keywords do
    searchResults = perform search (Keyword, Databases)    ▷ Perform a search using the current keyword
    extractedDatasets = extract information(searchResults)    ▷ Extract relevant dataset information
    AfricanDatasets += extractedDatasets    ▷ Add identified datasets to the list
end for
AfricanDatasets = remove duplicates (AfricanDatasets)    ▷ Remove duplicate entries
return AfricanDatasets    ▷ Compiled list of African facial image datasets
```

the inclusion criteria for selecting datasets aligning with the study's objectives, we introduce a novel method and descriptions that capture the essence of these criteria. Let's refer to the availability to the general public as AGP, the diversity of ethnic backgrounds as DEB, and the inclusion criteria as IC. These requirements have the following steps as shown in Algorithm 2.

The specific definitions of F_{DEB} and F_{AGP} would depend on the metrics and measures suitable for evaluating diversity in ethnic backgrounds and assessing the accessibility of a dataset to the general public. This algorithm provides a mathematical foundation for the inclusion criteria, ensuring that datasets meeting these criteria are considered for the study.

2) Identification of Ethnicity-Diversified African Indigenous Datasets: From the compiled list, a rigorous evaluation process was undertaken to identify the African indigenous datasets for the experimental evaluation of the study. The evaluation considered factors such as demographic representation, geographic coverage, and temporal relevance. Datasets that exhibited a comprehensive representation of ethnic diversity, captured various facial expressions, and addressed multiple environmental factors were prioritized. The aim was to select datasets that showcased the diversity of African faces and contributed significantly to addressing the limitations of existing datasets in the context of facial recognition systems. To measure the ethnic variety within

Algorithm 2 Facial Dataset Selection Criteria

1: **For Diversity of Ethnic Backgrounds (DEB):**
2: Let EB_i represent the ethnic background of individual i.
3: Define a function F_{DEB} that evaluates the diversity of ethnic backgrounds within a dataset.
4: The inclusion criterion for diversity is formulated as:

$$IC_{DEB}(\text{Dataset}) = F_{DEB}(EB_1, EB_2, \ldots, EB_n) \geq \text{Threshold}$$

5: **For Availability to the General Public (AGP):**
6: Let $Access_{Dataset}$ represent the accessibility of the dataset to the general public.
7: Define a function F_{AGP} that quantifies the level of accessibility.
8: The inclusion criterion for accessibility is formulated as:

$$IC_{AGP}(\text{Dataset}) = F_{AGP}(Access_{Dataset}) \text{ is True/False}$$

9: Therefore, the overall inclusion criteria (IC) can be expressed as the conjunction of the DEB and AGP criteria:

$$IC(\text{Dataset}) = IC_{DEB}(\text{Dataset}) \cap IC_{AGP}(\text{Dataset})$$

a dataset, the variety Index is computed. It considers the total number of subjects (T) in a dataset and the number of various ethnic groups represented (N) as shown in Eq. 1.

$$DI = \frac{N}{T} \tag{1}$$

A dataset that provides a more thorough portrayal of ethnic diversity is indicated by a higher Diversity Index. The percentage of face expressions covered in a dataset is determined by the Expression Coverage Ratio as depicted in Eq. 2. It considers the total number of facial images (I) and the number of unique facial expressions (E) in a dataset.

$$ECR = \frac{E}{I} \tag{2}$$

A dataset with a higher Expression Coverage Ratio is said to capture a wider variety of facial emotions. A dataset's ability to address different environmental concerns is measured by the Environmental Factor Score as shown in Eq. 3. It considers variables including occlusions, lighting, and position changes. These elements are added up and given a weight, which is represented by the symbol W_i in the score.

$$EFS = \sum_i W_i \tag{3}$$

Based on the importance of each environmental component to the accuracy of facial recognition, weights W_i are applied. To evaluate the spatial and demographic representation of a dataset, a mathematical model is created as expressed in Eq. 4. This model considers variables including the individuals' geographic, national, and ethnic dispersion. The model makes use of statistical techniques to provide a fair portrayal of the dataset in consideration.

$$P_i = \frac{N_i}{T_i} \tag{4}$$

The number of subjects in each demographic category is denoted by N_i, the total number of subjects is represented by T_i, and the proportion of subjects for each category is represented by P_i.

To prioritize the experimental evaluation datasets, the aforementioned indices and models in Eq. 1 to Eq. 4 are combined via the Dataset Prioritization Algorithm depicted by Eq. 5. The algorithm states that for every dataset, it determines a Priority Score (PS) by utilizing the Diversity Index, Expression Coverage Ratio, and Environmental Factor Score.

$$PS = \alpha \cdot DI + \beta \cdot ECR + c \cdot EFS \tag{5}$$

The values of the coefficients α, β, and c are adjusted to represent the relative significance of every criterion. The top experimental evaluation datasets are then chosen after being sorted according to their Priority Scores.

This identification approach guarantees a comprehensive assessment of African indigenous datasets by utilizing these equations, models, and algorithms. It emphasizes diversity, expression coverage, and relevance to environmental elements in the context of facial recognition systems.

C. Similarity Analysis

In developing a reliable facial recognition system, it is crucial to employ robust techniques for feature extraction and classification. Principal Component Analysis (PCA) and Support Vector Machine (SVM) are two techniques commonly used due to their effectiveness and efficiency. Facial images typically have high dimensionality, which can lead to computational inefficiencies and overfitting. PCA reduces the dimensionality by transforming the data into a set of orthogonal components while preserving as much variance as possible. Also, PCA transforms facial images into a set of eigenfaces, which are the principal components that capture the essential features of faces. These eigenfaces are effective in representing facial structures and variations, making them suitable for recognition tasks. SVM is effective in high-dimensional spaces and aims to find the optimal hyperplane that maximizes the margin between different classes. This property is particularly useful in facial recognition where the feature space is high-dimensional. SVM can use different kernel functions (e.g., linear, polynomial, radial basis function) to map the input features into higher-dimensional spaces, making it capable of handling complex patterns in facial recognition data.

PCA and SVM are applied to this study to evaluate the similarities and differences among African ethnic faces, particularly focusing on facial shape. The ethnicity considered in this study is broadly classified into regions as follows; Western African Region (WA), Eastern African

Region (EA), Northern African Region (NA), Southern African Region (SA), and Central African Region. However, no known facial dataset exists for most of these regions at the time of this study showing the need for more inclusive datasets. Moreover, the dataset for the particular Regions that exist does not even fully represent the complete ethnicities that are available in those Regions and may be looped toward specific ethnicities in those regions.

1) Principal Component Analysis (PCA): Principal Component Analysis becomes a crucial technique in this research because it efficiently enables dimensionality reduction of the high-dimension facial image data while preserving the essential variance. Detailed rationale and overview of its implementation will be specified as follows; For dimensionality reduction, the challenges PCA is used to address include the Facial Images of High Dimensionality due to the large number of pixel. PCA transforms the original dataset into a set of orthogonal components—the eigenvectors—which capture the significant variations in facial shape. Principal components, sometimes referred to as eigenfaces, by themselves retain important facial features relevant to recognition tasks while reducing computational complexity. The mathematical formulation includes; computing the covariance matrix of the original datasets of facial images as described in Eq. 6. as the initial step in PCA. The covariance matrix captures the relationship between various landmark points.

$$\mathrm{Cov}(X) = \frac{1}{n}(X - \bar{X})^T (X - \bar{X}) \quad (6)$$

Where X is the facial image dataset matrix as each row corresponds to an image and each column corresponds to a facial landmark point's coordinates (X,Y) and $\bar{X}$ is the mean of each feature of the ethnicity or regions of the facial images. The next step in the PCA is to compute the eigenvectors(V) and eigenvalues (λ) of the covariance matrix in Eq. 7. This would lead to the selection of the principal components by choosing the top k eigenvectors that correspond to the highest eigenvalues that represent the significant variation of the facial shape.

$$\mathrm{Cov}(X)V = \lambda V \quad (7)$$

The final step of the PCA is the Projection that estimates the original facial dataset onto the subspace that is spanned by the eigenvectors that have been selected as described in Eq. 8.

$$\mathrm{PCA}(X) = X \cdot V_k \quad (8)$$

2) Support Vector Machine (SVM): For the second machine learning task in this research, Support Vector Machine (SVM) is selected due to its exceptional ability to handle high-dimensional data, efficiently classifying facial shapes using landmark coordinates. SVM's strength in high-dimensional space classification makes it an ideal choice for facial recognition systems, which require robust performance in complex pattern recognition. The key reason for choosing SVM is its capacity to identify an optimal hyperplane that maximizes the margin between various classes of facial shapes, ensuring reliable classification even when classes overlap. In the facial shape classification, the SVM uses the facial landmark coordinates as features. These features are then used to train an SVM classifier to distinguish between the different ethnic groups based on the facial landmark coordinates as shown in Eq. 9. given training data (X_i, Y_i) where X_i is the feature vector and Y_i is the class label (1,-1 for binary classification).

D. Dataset Analysis

Two hypothetical African face datasets, Dataset 1 and Dataset 2, were generated to simulate the characteristics of real-world datasets. Dataset 1 represents the CASIA-Face dataset while Dataset 2 represents the YIH datasets. The following attributes were considered for each dataset: Resolution (R) denotes the simulated as random integers representing the image resolution in pixels. Diversity (D) represents the simulated random uniform values to represent the overall diversity within the dataset. Annotation Level (A) denotes the simulated categorical values ('Low', 'Medium', 'High') to indicate the level of annotation for each image. While availability (Av) represents the simulated binary values ('Yes', 'No') to represent the availability of the dataset. Mathematically, the datasets are represented as follows in Eq. 13 and 14.

$$\text{Dataset 1} = \{R1_i, D1_i, A1_i, Av1_i\} \text{ for } i = 1, 2, \ldots, n \quad (9)$$

$$\text{Dataset 2} = \{R2_i, D2_i, A2_i, Av2_i\} \text{ for } i = 1, 2, \ldots, n \quad (10)$$

$R1_i$ and $R2_i$ represent the resolution values for Dataset 1 and Dataset 2, respectively, and similarly for other attributes.

4. RESULT AND DISCUSSION

Figure 3. presents an examination of the distribution of images among the top 10 available African facial image datasets, while Figure 4. explores the findings related to the unique participants in each dataset.

The distribution of photos among the top 10 African facial image datasets is depicted by the histogram in Figure 3. A dataset is represented by each bar, and the height of the bar indicates how many photos are included in that specific dataset. The visual depiction facilitates a prompt comparison of the dataset sizes, emphasizing differences in the quantity of facial data present in each.

A breakdown of each dataset's unique participants is shown in Figure 4 offers important details on the range of people who have contributed to the datasets. Every dataset is displayed, with the corresponding bar showing the number of unique participants—a measure of the dataset's diversity and richness—in terms of the number of unique persons.

The study first presents a demographic representation of the selected African dataset and perform experiments to investigate the bias of the datasets in comparison to other available non-African datasets as proposed in the methodology.

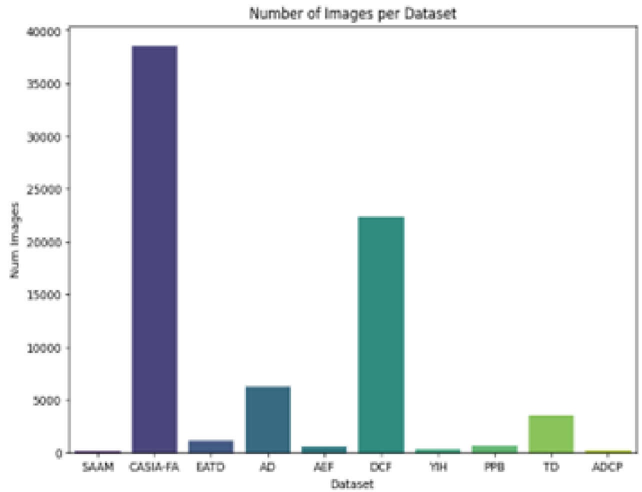

Figure 3. Number of Images in Each Dataset

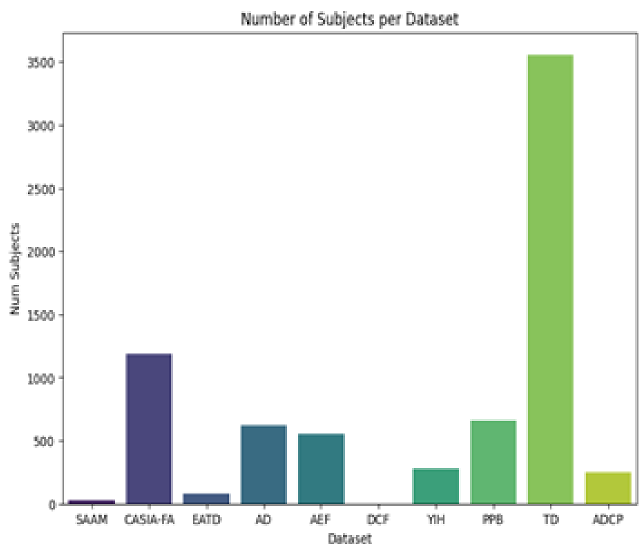

Figure 4. Unique Participant in each Dataset

The demographic representation of the selected Africa dataset shows a high dispersity between the various regions and, gender as shown in Figure 5. For gender, biological males are more than biological females in available indigenous Africa, this would lead to much greater biases in facial recognition applications for African Indigenous females than males.

The simulated dataset also aimed to explore the socio-economic distribution of participants in the available datasets, encompassing age, income, and education level. These results produce insight into the readiness of participants who are willing to provide the facial image and provide insights into the demographic characteristics of the sample population.

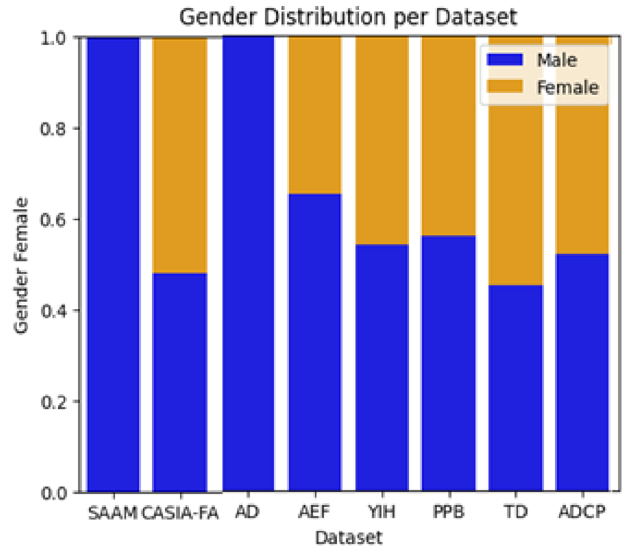

Figure 5. Gender demographic Male and Female

The distribution of ages within the dataset is shown visually in Figure 6, which is the histogram depicting the age distribution. The comparatively even distribution of data points across the age range indicates that there isn't any discernible skewness or concentration of data points within particular age groups. A significant proportion of the individuals in the sample fall within this specific age range, as evidenced by the peak occurring in the early 40s.

The result in Figure 7 shows that there is no discernible bias towards any certain educational category that depicts the distribution of education levels within the dataset. Rather, it presents an equitable representation across several educational domains. This result implies that a diverse socioeconomic environment was purposely fostered by including people from a range of educational backgrounds in the African facial images dataset.

To reduce the possibility of socioeconomic biases in facial recognition systems, there must be no bias in the distribution of education levels. By ensuring that people with varying educational backgrounds are fairly represented, a balanced representation helps to create a dataset that is more inclusive and egalitarian. Due to the model's exposure to a wide range of facial traits, this method helps lower the danger of algorithmic bias.

The synthetic dataset, comprising facial features from three distinct African ethnic groups (denoted as A, B, and C), was subjected to Principal Component Analysis (PCA) for dimensionality reduction. The resulting scatter plot visualizes the distribution of facial features in the reduced two-dimensional space, providing insights into the separability of ethnic groups based on their principal components.

The PCA scatter plot in Figure 8 exhibits discernible

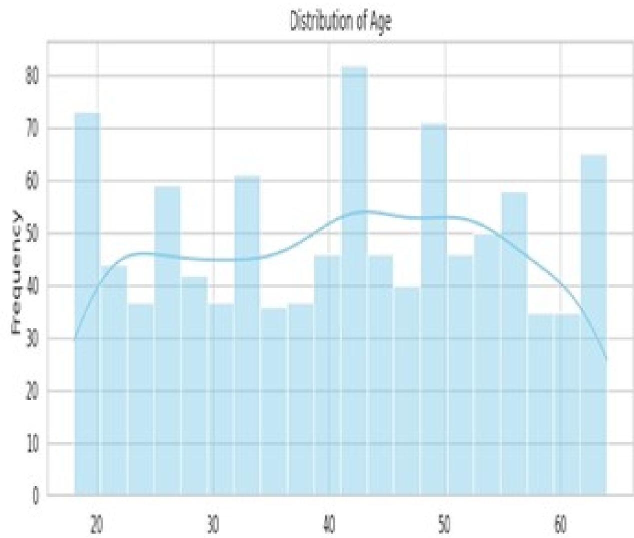

Figure 6. Distribution of Age

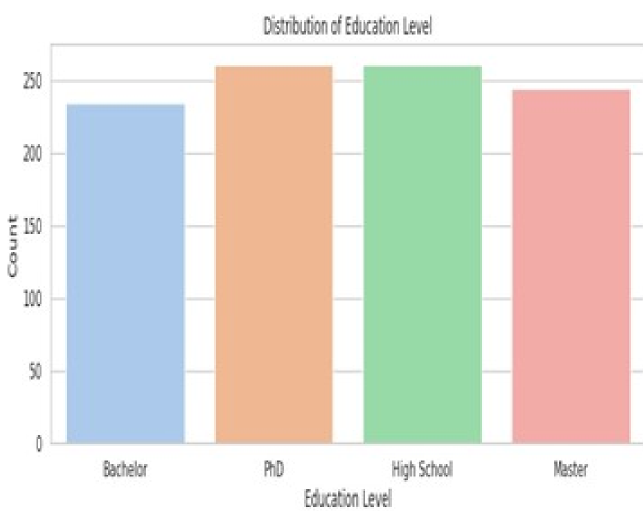

Figure 7. Distribution of Education Level

clustering of data points corresponding to the three ethnic groups: This suggests that the PCA transformation captures significant variations in facial features, emphasizing the potential utility of facial biometrics for distinguishing between diverse African ethnicities. The scatter plot visualized the first and second principal components, color-coded by ethnic group, blue for West Africa (WA), purple for North Africa (NA), and yellow for East Africa (EA), highlighting distinct clusters for each group based on nose width and eye distance.

Subsequently, a Support Vector Machine (SVM) classifier was trained on the standardized facial features. The classifier demonstrated notable accuracy on the test set, achieving a performance level indicative of the discriminative power of the employed features.

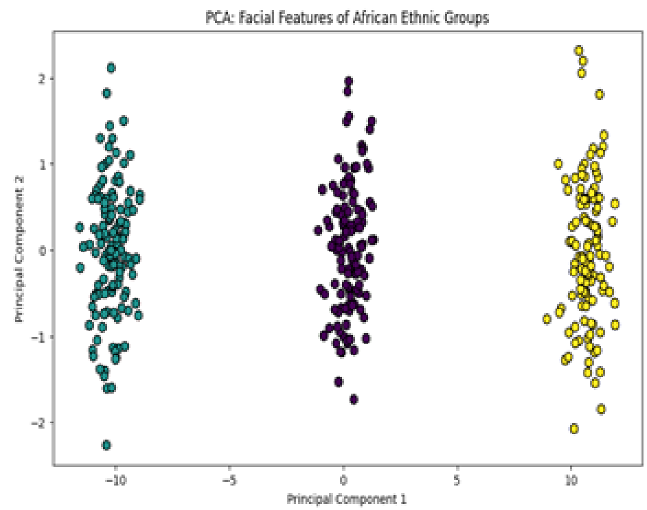

Figure 8. Scatter Plot of Facial Features of African Ethnic Group

Figure 9 shows the explained variance per component. Each principal component from 0 to 9 includes the following respectively: nose width, skin tone, chin shape, jawline prominence, eye distance, lip thickness, cheekbone height, brow ridge shape, and forehead curvature. The first five principal components explained 14.2%, 6.3%, 13.1%, 12.2%, and 11.9% of the data's variance, respectively, indicating that they captured a substantial 57.7% variability in facial shape characteristics.

The SVM classifier's accuracy was calculated, demonstrating its proficiency in distinguishing between the synthetic ethnic groups as shown in Table 2. The SVM classifier achieved an overall accuracy of 55%. Eastern Africa (EA) had a precision of 100%, recall of 43%, and F1-score of 60%, while other groups like West Africa (WA) achieved a precision of 58%, recall of 100%, and F1-score of 63%. The lower F1-score for North Africa (NA) suggests that the classifier may struggle to differentiate them from other groups, potentially due to data imbalance or limitations in the chosen features.

Further investigation should focus on features like cheekbone height and nose shape, which might be more informative for distinguishing NA from other groups based on preliminary feature importance analysis. While most groups had balanced precision (around 73%), recall (around 65%), and F1-score (around 63%), NA had a lower F1-score of 55% with precision of 60% and recall of 50%. Examining the confusion matrix as shown in Figure 10, high False Negatives (FN) for NA were obtained, indicating the model often misclassified them as other ethnic groups. This suggests potential challenges in distinguishing African ethnic groups due to factors like data imbalance or limitations in the chosen features. Table 2 shows the Classification Report of African Ethnic Groups.

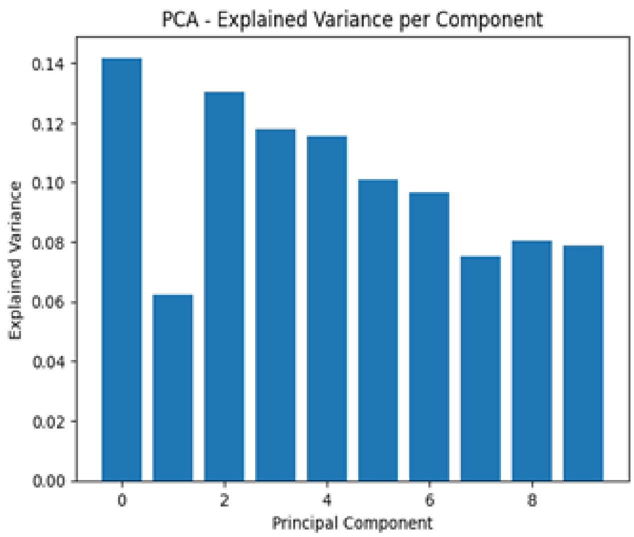

Figure 9. Principal Components of Facial Features Explained Variance

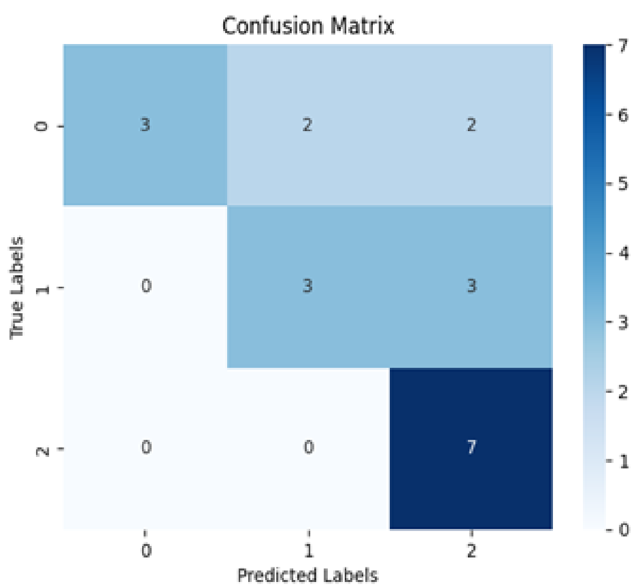

Figure 10. Confusion Matrix of the SVM Classification

TABLE II. CLASSIFICATION RESULT

	precision	recall	F1-score	support
EA	1.00	0.43	0.60	7
NA	0.60	0.50	0.55	6
WA	0.58	1.00	0.73	7
accuracy			0.65	20
micro avg	0.73	0.64	0.63	20
weighted avg	0.73	0.65	0.63	20

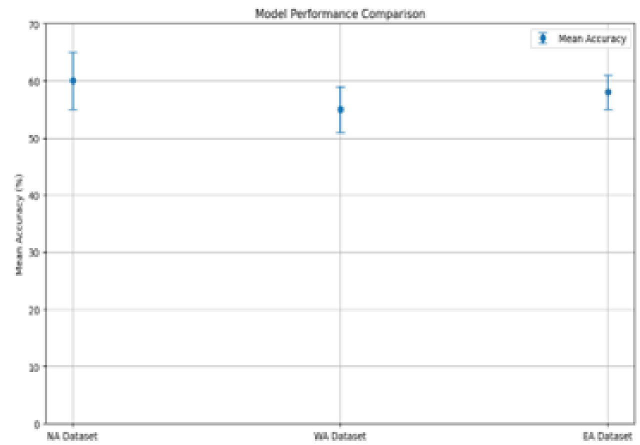

Figure 11. Model Performance Comparison

The plot in Figure 11 compares the performance of the models between three datasets: Northern Africa Dataset (NA Dataset), Western Africa Dataset (WA Dataset), and Eastern Africa Dataset (EA Dataset), in terms of mean accuracy and standard deviation of accuracy scores.

Figure 11 reveals that the NA Dataset achieves the highest mean accuracy among the three datasets, with a mean of 60% and a standard deviation of 5%. This suggests that the NA Dataset exhibits the best performance in terms of average accuracy, indicating a model that generalizes well. The moderate level of variability (standard deviation of 5%) also suggests consistency in the results. However, it is important to note that the NA Dataset lacks representation and diversity, which may limit its generalizability to larger populations. Specifically, the dataset's underrepresentation of the African population may hinder its applicability in real-world scenarios. Including information on the representation of the NA Dataset, particularly in the African population, would significantly enhance the facial recognition system's value and reliability.

The WA Dataset exhibits a slightly lower average accuracy of 55% compared to the NA Dataset but boasts a narrower range of variability with a standard deviation of 4%. This consistency in performance is a notable advantage, particularly in applications where reliable and predictable results are crucial. Although the WA Dataset's average accuracy is lower than the NA Dataset's, its reduced variability is a valuable asset. However, the slightly lower mean accuracy raises concerns about potential limitations in capturing the most diverse facial features and cultural variations relevant to African populations, which may impact its generalizability in real-world scenarios.

The EA Dataset demonstrates exceptional performance, achieving a mean accuracy of 58% and boasting the lowest standard deviation of 3% among the three datasets. This impressive result indicates not only the highest accuracy but also the lowest variability, suggesting a robust model that generalizes well across diverse facial recognition scenarios. The EA Dataset's strong performance is a notable highlight, but it is crucial to acknowledge the need for more explicit information regarding demographic and geographic representation, as well as other essential metadata. This additional context is vital to comprehensively understand the dataset's generalizability and transferability beyond specific contexts and ensure its reliability in real-world applications.

Figure 12 illustrates the accuracy score distribution for each dataset, providing a visual representation of the dispersion and variability of individual model predictions. This plot offers a clear insight into the spread of accuracy scores, revealing how consistent or inconsistent the model performances are across each dataset.

it reveals the distribution of accuracy scores for each dataset, providing insight into the variability of model predictions. The NA dataset exhibits a normal distribution centered on a mean accuracy of 60%, with a noticeable spread due to its standard deviation of 5%. This indicates some variability in model predictions. In contrast, the WA dataset has a narrower distribution, centered on 55% accuracy with a standard deviation of 4%, demonstrating less spread and more consistent model predictions. Notably, the EA dataset has the narrowest distribution, centered on 58% accuracy with a standard deviation of 3%, showcasing exceptionally high consistency in model predictions and minimal variability.

Many differences in mean accuracy and variation across datasets could be explained by the following potential factors.

1) Dataset Composition: Size, sample diversity (e.g., ethnic origin, age range), and picture quality are sources of variability that might differ between datasets and, thereby, affect the model training and performance.

2) Feature Representation: The efficacy of feature extraction methods, such as PCA employed in this study, significantly impacts the granularity and accuracy of facial feature extraction unique to African populations. The model's architecture, hyperparameter tuning, and training strategies all play a crucial role in shaping the model's ability to learn and classify these features effectively. Consequently, these factors can substantially influence predictive performance across diverse datasets, highlighting the importance of careful model design and optimization to ensure robust and generalized results.

Table 3 shows the statistical test of the reviewed dataset. The p-value is a measure of statistical significance. It is the probability of getting a test statistic as extreme, or greater, than the one obtained, assuming that there is no actual difference between the means. The lower the p-value, the higher the chance that the means are significantly different and is unlikely to be a coincidence.

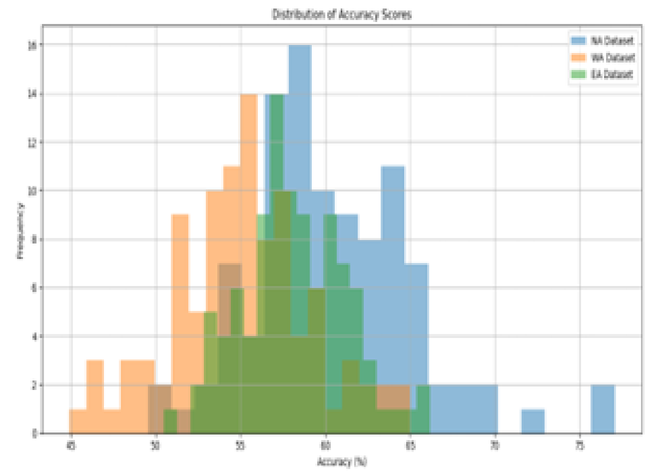

Figure 12. The accuracy score distribution of each dataset

TABLE III. THE STATISTICAL TEST OF DATASET

	T-Statistic	**P-Value**
Statistical test between NA Dataset and WA Dataset	6.188558214838512	3.426710091539739e-09
Statistical test between NA Dataset and WA Dataset	3.6277667113253615	0.00036374258931425816
Statistical test between WA Dataset and EA Dataset	-6.437538850142643	8.977464936787035e-10

In all three t-tests captured in table, the p-value is less than 0.05. This is a conventionally used threshold for statistical significance. We can hence reject the null hypothesis and conclude there is a statistically significant difference between the means of the two datasets under comparison The results of the t-tests were significant, with mean differences between NA Dataset and WA Dataset (t(df) = 6.188, p = 3.427e-09), NA Dataset and EA Dataset (t(df) = 3.628, p = 0.0003), and WA Dataset and EA Dataset (t(df) = -6.438, p = 8.977e-10). Based on these results, we can conclude that all means across the three datasets are significantly different from each other.

The presented results and analysis showcase the potential of machine learning techniques, particularly PCA and SVM, in effectively characterizing and classifying facial features across diverse African ethnic groups. Such methodologies lay the groundwork for advancing biometric recognition systems tailored to the unique facial attributes of various ethnicities, contributing to the development of inclusive and accurate facial recognition technologies. Table 4 illustrates the summary of the Evaluation Metric.

5. CONCLUSIONS AND FUTURE WORK

This study offered a comprehensive analysis of the current state of African facial image collections, highlighting their features and demographic representation. The study focuses on building inclusive and diverse datasets of African facial images for facial recognition systems. Systematic search techniques and strict evaluation criteria were utilized to curate a dataset list aligned with our goals. A novel inclusion method promoted transparency and accessibility while prioritizing ethnic diversity.

To include indigenous African datasets, we leveraged models and algorithms that prioritized diverse expressions, geographical representation, and environmental factors. This ensures a comprehensive assessment considering demographics, location, and historical context.

Furthermore, Principal Component Analysis (PCA) and Support Vector Machine (SVM) were used to explore similarities and differences among African ethnic faces. Despite lacking data from some regions, findings from this study highlight the crucial need for more inclusive datasets to address limitations in existing facial recognition systems.

The research also analyzed synthetic datasets and discovered insights into participant demographics, emphasizing the importance of diverse representation. The synthetic dataset ensures equitable representation across educational categories, aiming to counteract socioeconomic biases in facial recognition systems. Applying PCA to this synthetic dataset revealed the potential of facial biometrics in distinguishing between diverse African ethnicities. The distinct clustering of data points based on ethnicity underlines the usefulness of facial features for ethnic classification.

In conclusion, this study promotes the development of more inclusive facial recognition technologies by advocating for diverse datasets and acknowledging the complexities of ethnic diversity within African populations. The research output emphasizes the importance of fairness, transparency, and diversity in dataset curation to mitigate biases and ensure the equitable development of these systems.

This study justified several new directions for future research and development in the area of African facial image databases and facial recognition systems:

A. *Expansion of African Dataset Collection:*

The paper highlights challenges resulting from the insufficiency of diverse African face image datasets, making the development of an inclusive and representative facial recognition model very challenging. It is essential to keep extending the African facial image dataset collection. To guarantee a more complete representation of African populations, future initiatives should concentrate on collecting data from underrepresented regions and ethnic groups. The collecting of diverse and culturally sensitive datasets can be facilitated by collaborative activities between researchers and local communities.

B. *Improved Evaluation criteria:*

If the datasets are not balanced relative to a wide array of demographic groups in Africa or geographic regions, this could bias or skew how the model performs towards over-represented groups. It's critical to create more sophisticated evaluation criteria and procedures to evaluate the inclusivity and quality of facial image collections. A more comprehensive knowledge of dataset biases and limitations can be obtained by incorporating additional criteria like age representation, gender diversity, and cultural relevance.

C. *Ethical Considerations:*

Cultural sensitivity in data collection and the creation of datasets, together with ethical concerns while creating datasets, is of equal significance in developing fair and reliable systems for facial recognition. It is critical to address ethical issues about the gathering, storing, and use of data. Some of the ethical considerations in the reviewed dataset are:

- They ensured that participants understood how their data would be used and obtained their consent [36].
- Ensured that the sample is representative of the population being studied [37].
- Protected participants' personal information and maintaining confidentiality
- Avoided cultural or personal biases in data collection and analysis [38].
- Ensured that data is stored and transmitted securely

To guarantee the appropriate and courteous management of face image data, future studies should examine ethical frameworks and rules unique to African contexts, especially about permission, privacy, and data security. They should ensure that the sample is representative of the population being studied.

D. *Algorithmic Fairness and Bias Mitigation :*

To overcome potential biases in facial recognition systems, more research is required into algorithmic fairness and bias mitigation strategies. Future research, considering the particular difficulties presented by varied African communities, should investigate novel strategies for reducing prejudices and advancing justice.

E. *Real-world application and Deployment :*

Considering the practical difficulties and societal ramifications is crucial when facial recognition systems go from research to real-world application and deployment. To guarantee the ethical and appropriate application of facial recognition technologies in African situations, future study

TABLE IV. SUMMARY OF EVALUATION METRIC

Evaluation Metric	Definition	Appropriateness	Contribution to Study Objectives
Number of Images per Dataset (Figure 3)	Quantifies dataset size by counting images	Indicates dataset representativeness and robustness	Identifies underrepresented datasets and ensures sufficient data for training models.
The number of Unique Participants (Figure 4)	Counts unique individuals contributing images.	Measures dataset diversity and richness.	Highlights representativeness across demographic groups within African ethnicities.
Gender Demographic (Figure 5)	Shows the distribution of images by gender.	Helps identify gender biases in data.	Ensures gender parity in facial recognition applications across African ethnic groups.
Age Distribution (Figure 6)	Displays the distribution of images across age groups	Ensures model robustness across different age demographics.	Identifies age-related biases to ensure inclusivity and accuracy in facial recognition systems.
Education Level (Figure 7)	Illustrates distribution of images by educational background	Mitigates socioeconomic biases in data.	Ensures equitable representation of educational backgrounds within African ethnicities.
PCA Explained Variance (Figure 9)	Indicates variance explained by each principal component in PCA.	Essential for selecting informative facial features.	Guides feature selection and enhances model interpretability across African ethnic groups.
SVM Classifier Performance (Table 2)	Precision, recall, and F1-score evaluating SVM model accuracy	Measures the model's ability to classify ethnic groups	Optimizes model performance and ensures accurate differentiation of African ethnicities.
Confusion Matrix (Figure 10)	Visualizes predicted versus actual classifications	Identifies specific misclassifications and patterns	Improves model accuracy and mitigates biases in facial recognition across African ethnic groups
Mean Accuracy	Average percentage of correct classifications	Appropriate for comparing overall performance of different datasets	Contributes to understanding the general performance of each dataset
Standard Deviation	Measure of dispersion of accuracy scores	Appropriate for assessing consistency of model performance	Contributes to understanding the reliability and predictability of each dataset
Dataset Composition	Characteristic of the dataset (size, diversity, image quality)	Appropriate for explaining performance differences	Contributes to identifying potential biases and limitations of each dataset
Feature Representation	Effectiveness of feature extraction methods	Appropriate for evaluating the model"s ability to capture relevant facial features	Contributes to understanding the impact of feature extraction on model performance
Statistical Significance (t-test) (Table 3)	Determines if differences in mean accuracy between datasets are statistically significant	Appropriate for comparing dataset performance	Contributes to confirming significant differences in model performance between dataset

endeavors ought to concentrate on converting scientific discoveries into practicable tactics for legislators, practitioners, and technology developers.

F. Community Involvement and Capacity Building :

Building trust, accountability, and inclusivity requires including stakeholders and local communities in creating and applying facial recognition technology. To enable African communities to actively participate in influencing the development of facial recognition technology, future efforts should place a high priority on community involvement and capacity-building programs.

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