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ADVANCING AFRICAN COMPUTER VISION: PROGRESS, CHALLENGES, AND PATHWAYS FOR GROWTH

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ABSTRACT

Computer Vision (CV), a rapidly evolving field within Artificial Intelligence (AI), holds immense potential for addressing a wide array of societal and economic challenges globally. While a significant portion of global CV research is concentrated in a few established regions, there is a burgeoning and distinct landscape of CV innovation emerging across the African continent. This comprehensive article provides an in-depth overview of the current state of computer vision research in Africa, strictly adhering to the IMRaD (Introduction, Methods, Results, and Discussion) format. It meticulously identifies key research areas, highlights unique contributions, explores the multifaceted challenges faced by researchers, and discusses promising opportunities for future growth and collaboration. By critically examining recent scholarly work and survey insights, this paper aims to illuminate the dynamic trajectory of computer vision research in Africa and underscore its growing significance in the global scientific and ethical discourse on AI. The findings reveal a problem-driven research agenda, a critical engagement with data and ethical considerations, and a strong emphasis on fostering intra-African and international collaborations to build sustainable research capacity.

Keywords: Computer Vision, Artificial Intelligence, Africa, Research Trends, Datasets, Ethical AI, Collaboration, Development, Remote Sensing, Healthcare, Agriculture, Bibliometric Analysis, African Researchers.

INTRODUCTION

Computer Vision (CV) stands as a foundational subfield of Artificial Intelligence (AI), empowering machines to perceive, process, and interpret visual data from the world, much like human vision. This capability enables a vast array of specialized tasks, including image classification, object recognition, image captioning, scene understanding, and motion tracking [12, 14, 23, 34]. Over the past decade, CV has undergone a revolutionary transformation, largely propelled by breakthroughs in deep learning, particularly convolutional neural networks (CNNs) [12, 23, 24], and the widespread availability of colossal datasets suchases ImageNet [14, 24]. These advancements have translated into real-world deployments across diverse sectors, fundamentally impacting everyday life from automated vehicles and medical diagnostics to remote sensing and smart agricultural systems [5, 11, 12, 14, 16, 17, 25, 26, 27, 34, 35, 38, 40, 41, 42, 43, 50, 51].

Despite the pervasive nature and global reach of AI and CV technologies, the distribution of research and development remains significantly uneven. Historically, contributions to top-tier publications and access to cutting-edge computational resources have been heavily concentrated in a few regions, leaving many parts of the world, including the African continent, underrepresented [13, 30, 39, 44]. This imbalance not only limits the participation of diverse voices in shaping these transformative technologies but also restricts the development of solutions tailored to unique local contexts and challenges.

However, a notable shift is underway. The African continent is increasingly asserting its presence in the global scientific landscape, demonstrating a consistent rise in scientific output and fostering robust research collaborations across various disciplines [13, 19, 21, 27, 30, 39, 44, 46, 47]. This growing momentum extends powerfully into the realm of emerging technologies like computer vision. African researchers are not merely adopting global CV techniques but are actively adapting and innovating, leveraging these technologies to address pressing local challenges and unlock novel opportunities pertinent to the continent's diverse socio-economic and environmental landscape [36]. The distinctive nature of CV research in Africa is often characterized by a pragmatic focus on localized problems, necessitating the creation of context-specific datasets, and operating within varying resource constraints [36, 41].

This article undertakes an extensive examination of the current state of computer vision research in Africa. Its primary objectives are multifaceted: to synthesize the existing body of knowledge, to categorize the key areas of CV application and innovation, to meticulously identify the prevalent structural barriers and unique challenges faced by African CV researchers, and to highlight the continent's distinct and burgeoning contributions to the global CV field. By adopting the structured IMRaD framework, this paper offers a rigorous and comprehensive analysis of this evolving research domain. It places particular emphasis on the critical importance of local context in problem formulation, the necessity of culturally relevant data, and the power of collaborative efforts—both intra-African and international—in shaping a more equitable, inclusive, and impactful future for computer vision research and its applications across the continent. Furthermore, this study delves into the critical discourse surrounding ethical AI, decolonization of technology, and the integration of indigenous knowledge systems, which are increasingly central to African approaches to computer vision.

2. Related Works

To contextualize our comprehensive survey on computer vision research in Africa, it is imperative to discuss existing related works. Our study distinguishes itself by not only analyzing publishing trends but also extensively cataloging datasets, categorizing research topics, and gathering direct insights from researchers regarding the structural barriers they encounter.

2.1. Bibliometric Studies in Africa

Numerous scientometric and bibliometric studies have previously investigated scientific publications from Africa. Some have provided a general overview of scientific output across the continent [39, 44], while others have focused on specific disciplines such as health sciences [21, 32] or the broader domain of open educational resources [46]. Early analyses, such as that by Pouris and Ho (2014) [39], indicated a predominant focus on international collaborations among African countries, often driven by the availability of resources and research interests outside the continent. This suggested a potential lack of robust intra-continental collaboration.

More recently, Turki et al. (2023) conducted a pertinent bibliometric study on machine learning for health in Africa [47]. Their findings revealed that Northern African countries historically contributed most significantly, though this trend has seen a gradual shift with increasing contributions from sub-Saharan Africa. Crucially, their work also confirmed a strong correlation between international funding and collaborations and the increase in African scientific output. Inspired by these prior efforts, our study extends this analytical approach specifically to the broader and more diverse field of computer vision, encompassing applications from medical imaging to remote sensing. While some bibliometric studies have focused on specific CV topics like convolutional neural networks [12] or water resource management applications [27], they generally lack a specific focus on the African context. Our work, in contrast, adopts a decolonial computer vision approach within a participatory framework, which necessitates a deep dive into the African landscape. Unlike conventional high-level bibliometric analyses that primarily identify publishing and collaboration trends, our study introduces an additional layer of analysis by leveraging large language models to parse publication abstracts, enabling the automatic cataloging of African computer vision datasets. This detailed approach provides a more granular understanding of the research ecosystem.

2.2. African Datasets Initiatives

To our knowledge, a comprehensive and centralized platform gathering African computer vision datasets and highlighting the overall state of CV research in Africa has been lacking. While data science competition platforms like Kaggle and Zindi serve as significant sources for many unofficial African datasets, they host competitions across various topics, not exclusively those with an African context. Our initiative is inspired by platforms like LANFRICA, which focuses on providing accessible African language datasets and natural language processing publications relevant to African languages. In this study, our primary focus is on computer vision datasets to enhance their accessibility.

Previous approaches to listing African CV datasets might have adopted a "top-down" strategy, starting with a predefined taxonomy and then attempting to gather related publications. We find this method potentially misleading as it may not accurately capture the nuanced African research landscape due to its dependence on pre-established, potentially non-representative categories. Consequently, we adopted a novel "bottom-up" approach. This involved gathering all Scopus-indexed African computer vision publications from the past decade, followed by classifying dataset papers using large language models and performing meticulous manual annotation of their categories. To the best of our knowledge, our study is the first to propose and implement such a bottom-up methodology for cataloging computer vision datasets with a specific regional focus on Africa.

2.3. Grassroots and Participatory Frameworks

The discourse surrounding Artificial Intelligence for Social Good (AI4SG) has gained considerable traction, with recent works critically evaluating its definition and project assessment methodologies. Bondi et al. (2021) proposed the PACT (People, Activities, Contexts, Technologies) framework, a participatory approach designed to foster capabilities within communities [8]. This framework provides guiding questions to help researchers evaluate the "goodness" of a project within a participatory context. This aligns closely with the growing calls for a "decolonial

AI" movement [7, 17, 31, 33, 49], which emphasizes the importance of participatory and community-based efforts in AI development [31].

Currin et al. (2023) presented a framework for grassroots research collaboration, contrasting top-down versus bottom-up approaches and describing various types of emergent grassroots communities [13]. These communities include affinity-based organizations (e.g., Women in Machine Learning, Black in AI), topic-based communities (e.g., Masakhane, SisonkeBiotik), and event-based initiatives (e.g., Deep Learning Indaba). Their proposed framework specifically focuses on African grassroots initiatives, detailing common values and participation roles within such communities. SisonkeBiotik, for instance, focuses on machine learning for health, with an initial project being a bibliometric study of African research in that domain [47]. Inspired by these impactful efforts, our study similarly aims to conduct a comprehensive analysis focused on the computer vision field.

However, unlike previous works, our study integrates these elements within a broader survey framework to catalog datasets, identify key research topics, and, critically, document researchers' perspectives on existing barriers in their field. Furthermore, we quantitatively assess inequities in research by analyzing African contributions to top-tier venues. This focus is particularly important as publishing in leading venues can significantly open doors to scholarships, research grants, and invaluable collaborations, thereby influencing African researchers' access to cutting-edge datasets and computational resources. While previous questionnaires have surveyed African scientists generally [19, 27], none have specifically delved into the intricacies of computer vision research, which is the core focus of our current investigation.

3. METHODS

This section delineates the rigorous methodology employed for gathering and analyzing data for our survey, with a primary focus on Scopus-indexed publications. Our comprehensive pipeline comprises four main stages: (i) automatic search query generation, (ii) data collection, (iii) data verification, and (iv) data classification and analysis. The field of computer vision is inherently broad and multidisciplinary, frequently overlapping with machine learning for health but extending to a vast array of other applications. To capture this diversity effectively, we aimed to collect three distinct types of data. The first is a comprehensive set of African publications broadly relevant to computer vision, referred to as the full data. The second is a more focused subset of African publications, filtered by the top-50 keywords in the computer vision field, designated as the refined data. Finally, we collected publications from globally recognized top-tier venues in computer vision, termed the top-tier set. The following subsections elaborate on each of these four stages and the specific collection strategies for each data set.

3.1. Query Generation and Data Collection

For the full publications set, our objective was to gather all Scopus-indexed African publications relevant to the general field of computer vision. The search query was meticulously constructed to restrict results to publications with at least one author affiliated with an African institution. The primary search keyword used was a combination of ("image" OR "computer vision") to ensure broad coverage of the field. We further refined the temporal scope, limiting the time interval from 2012 to 2022. This period was chosen to align with the advent and significant impact of the deep learning era, notably marked by the convolutional neural networks' breakthrough victory in the 2012 ImageNet challenge [14, 24]. This comprehensive full set comprised approximately 63,000 publications. Due to its extensive scale, a full manual verification of this set was impractical. However, it served as a robust foundation for providing insights into the broad topic distribution across various African regions.

The refined publications set was designed to be a more manageable subset, allowing for a thorough verification phase. For this set, we exclusively focused on the top-50 keywords frequently utilized in computer vision publications globally. This targeted approach reduced the dataset to approximately 18,000 publications. Similar to the full set, the search query for the refined set was restricted to publications from African countries. The search keyword structure for this set was ("image" OR "computer vision") AND (KEYWORD), where KEYWORD was iteratively replaced with noun phrases derived from the identified top-50 computer vision keywords. Examples of such keywords included "deep learning," "object detection," "image segmentation," and "robotics." The selection of these top-50 keywords was facilitated by an off-the-shelf tool, as detailed later in Section 3.3. This refined and reduced dataset was critical for conducting a subsequent, more detailed verification to eliminate false positives. False positives could arise from publications being erroneously categorized as relevant to computer vision or incorrectly attributed to African authorship.

Finally, the top-tier publications set was specifically curated to assess African contributions to the most prestigious and influential venues in the computer vision field, without any geographical restrictions on the venues themselves. We utilized the CORE system (http://portal.core.edu.au/conf-ranks/) to identify A* and A-ranked computer vision conferences and journals. Additionally, several machine learning venues known for including significant computer vision publications were also included. The conferences selected for this set comprised: CVPR (Conference on Computer Vision and Pattern Recognition), ICCV (International Conference on Computer Vision), ECCV (European Conference on Computer Vision), ICML (International Conference on Machine Learning), ICLR (International Conference on Learning Representations), and NeurIPS (Conference on

Neural Information Processing Systems). To specifically capture contributions in medical image processing, MICCAI (Medical Image Computing and Computer Assisted Intervention) was also included. For journals, we focused on TPAMI (IEEE Transactions on Pattern Analysis and Machine Intelligence) and IJCV (International Journal of Computer Vision). The final top-tier set consisted of approximately 45,000 publications. While acknowledging that some publications within ICML, ICLR, and NeurIPS might encompass general machine learning topics beyond strict computer vision, their inclusion provides valuable statistical insights into the overall engagement and contribution of African institutions within these leading research forums. A verification process was also applied to this set to remove irrelevant publication types, such as "Retracted" or "Review" articles, ensuring that the analysis focused solely on original research contributions.

Throughout the data collection stage for both the refined and top-tier sets, we primarily leveraged Scopus APIs (https://pybliometrics.readthedocs.io/en/stable) for efficient and structured data retrieval. While SciVal (https://scival.com/home) was mildly used for the initial selection of the top-50 keywords and aspects of the full set collection, its usage was constrained by limitations such as restricted control over time intervals and the granularity of retrieved metadata, particularly author countries and affiliation histories.

3.2. Data Verification

A crucial phase of our methodology involved rigorous data verification to minimize sources of error and ensure a precise understanding of African computer vision research. Given the extensive and diverse nature of the computer vision field, this verification was paramount. While the full set (approximately 63,000 entries) was too large for exhaustive verification, our efforts were concentrated on the refined and top-tier sets, where accuracy was critical for subsequent detailed analysis.

Our decision to implement a robust initial verification phase stemmed from identifying three primary sources of errors within the collected refined and top-tier datasets:

(i) African Authorship Errors: These errors involved misattribution of African affiliation. For instance, in multiple publications, Papua New Guinea was mistakenly classified as an African country, conflating it with Guinea. Other examples included typographical errors in country names, such as "Swaziland" being incorrectly recognized as "Switzerland."

(ii) Computer Vision Relevance Issues: This category encompassed publications whose content was deemed irrelevant to computer vision despite containing trigger keywords. A common example was the use of the term "image data" in an abstract when the publication's core focus was on a simulated milling circuit dataset, having no actual relevance to image interpretation or processing in a CV context.

(iii) Irrelevant Publication Types: Our initial queries sometimes retrieved publication types that were not original research articles. These included "Retracted," "Review," "Erratum," or "Conference Review" types, which needed to be filtered out to maintain the focus on primary research contributions.

Examples of publications rejected during our verification phase due to these error sources are made available in our code repository (https://github.com/Ro-ya-cv4Africa/acvsurvey/). Our definition of "relevance to computer vision" was broad: we considered any work that operated on image datasets with the explicit aim of interpreting or processing these images as relevant.

The verification process for computer vision relevance commenced with an automatic filtering step. We excluded venues with fewer than ten publications if their names did not belong to our predefined list of top-tier venues and did not explicitly contain the keywords "image" or "computer vision." While this might result in some false negatives (i.e., relevant publications being filtered out), we prioritized reducing false positives within the refined set to enhance its quality. The remaining venues were then manually inspected to identify any that appeared irrelevant to the computer vision domain. From these potential irrelevant venues, we randomly sampled publications and manually reviewed their titles and abstracts to definitively determine their relevance to computer vision.

Additionally, we meticulously verified publications' authors and affiliations to confirm the inclusion of at least one African institution. This began with an automatic verification of the countries listed in the affiliations, which helped flag initial false positives like Papua New Guinea. This automatic check was complemented by randomly sampling publications for manual inspection of author affiliations. Finally, to ensure our focus on original research, we systematically filtered out publication types such as "Retracted," "Editorial," "Review," "Erratum," and "Conference Review." Following this rigorous verification phase, the final refined set comprised approximately 12,000 high-quality publications. Comprehensive metadata for all authors in both the refined and top-tier sets were retrieved for subsequent analysis.

3.3. Data Classification and Analysis

This section describes our distinctive "bottom-up" approach for the identification and annotation of African publications focused on computer vision datasets, a method that intentionally diverged from traditional "top-down" data collection strategies relying on predefined categories.

The initial phase involved the automatic identification of potential dataset papers. We leveraged large language models (specifically, the GPT series [10]) to analyze the abstracts of publications within our collected sets. This automated process was instrumental in efficiently gathering a comprehensive range of African computer vision dataset publications, which were subsequently categorized as "official datasets" (i.e., formally published). This extensive collection provided a broad and inclusive foundation for the subsequent, more granular annotation process. In parallel, a collection of "unofficial datasets" was compiled. These included datasets gathered from challenge websites and data hosting platforms that, while widely used, were not formally published as academic papers. This manual compilation spanned the last five years, capturing valuable, practical data initiatives.

The core of our bottom-up approach lay in the annotation and categorization phase. Each dataset publication underwent a meticulous manual annotation process, during which two descriptive labels were assigned by expert annotators. These labels could either be chosen from a predefined list or independently created by the annotators, allowing for flexible and emergent categorization that accurately reflected the nuances of African CV research. The initial predefined list of categories was derived from those used in the CVPR conference's call for papers (https://cvpr.thecvf.com/Conferences/2023/CallForPapers), which was then systematically augmented with additional categories identified and proposed by our annotators. This hybrid approach ensured a comprehensive yet computer vision-focused overview of the field in Africa, contrasting with broader top-down classification systems like the ACM Computing Classification System, which covers the entire computing field. Our annotator pool consisted of PhD students and post-doctoral researchers with specialized expertise in relevant fields, including computer vision, medical image processing, and neuroscience. These annotators were tasked with labeling the datasets based on their abstracts (for official publications) or descriptions (for unofficial datasets). The annotation process was iterative: initial guidelines were refined based on annotators' feedback after the first ten entries, leading to a continuously improving classification system. Crucially, each dataset publication was annotated independently by two separate annotators. In instances of conflict between their assigned labels, a third, senior researcher acted as a tie-breaker, providing the final, authoritative labels for the dataset.

Ethical considerations were a significant and integrated aspect of our methodology. Annotators were specifically instructed to identify any datasets that raised ethical concerns, such as potential privacy violations, issues related to the "right to be forgotten," or any other sensitive data practices. Our approach was inclusive, allowing for the categorization of papers that did not directly propose new datasets but rather augmented or re-analyzed existing ones. Additionally, datasets originating from African institutions but not exclusively focused on African subjects were included, with appropriate notes for clarification to maintain transparency regarding the data's geographical relevance.

The culmination of this meticulous process was the development of a comprehensive taxonomy of African datasets in computer vision. This taxonomy, informed by a flexible, inclusive, and ethically aware approach, serves as a valuable resource for current research and establishes a foundational framework for future explorations and data-driven initiatives in the field.

Beyond the identification and categorization of datasets, we conducted three additional forms of analysis on the full publications set:

(i) Topic Analysis: This analysis aimed to identify the most prevalent computer vision research problems tackled across the African continent and their regional distribution. We leveraged the keywords associated with each publication and utilized SciVal (https://scival.com/home), an off-the-shelf tool that employs a standard clustering procedure, to retrieve the top three keywords under the "Topic Name" for each publication. This provided insights into top research topics and their regional trends.

(ii) Geo-temporal Analysis: This form of analysis examined the publishing patterns of the five defined African regions over time, providing insights into growth and distribution.

(iii) Collaboration Patterns Analysis: We contrasted the trends of collaborations occurring solely between African countries versus those involving international partners, shedding light on the nature of research networks.

3.4. Ethical Considerations in Study Design

Beyond the ethical considerations integrated into the data annotation process, it is important to acknowledge broader ethical implications within our study design and data collection. Our exclusive reliance on Scopus-indexed publications introduces an inherent bias towards the English language. This is a significant limitation, as French is widely spoken and used in academic discourse across numerous African countries. Similarly, publications in various indigenous African languages, which might contain valuable research, are unfortunately not captured by our dataset. This language bias inevitably creates a partial view of the total research output, potentially underrepresenting contributions from regions where English is not the primary academic language.

Furthermore, the high publishing costs associated with many Scopus-indexed venues can create substantial barriers for researchers in lower-income regions, particularly within Africa. This economic hurdle may compel African researchers to publish more frequently in alternative, non-Scopus-indexed venues, further contributing to the underrepresentation in our dataset. Our research team, however, was intentionally composed of researchers from diverse African countries, including Nigeria, Cameroon, Benin, Egypt, Tunisia, Tanzania, and Ghana, spanning four African regions (Western, Northern, Eastern, and Central). This team composition directly aligns with our overarching goal of improving equity in research within Africa, by bringing multiple regional perspectives to the interpretation and analysis of the data. Despite these limitations, our systematic approach provides valuable insights into the documented, accessible research landscape.

3.5. Manual Validation Results

To ensure the reliability and validity of our refined dataset, we conducted a rigorous manual validation process. A random sample constituting 5% of the refined set of publications was selected for independent manual verification by our research team. Each paper in this sample was assigned to two annotators.

For topic verification, annotators meticulously reviewed the abstract of each selected publication to confirm its relevance to computer vision. Our results demonstrated a high accuracy rate of 91.1%, indicating that only 8.9% of the publications were erroneously assigned as computer vision-related. This suggests a robust initial automatic filtering and classification.

For authorship verification, annotators carefully scrutinized the affiliations of all authors to ensure that at least one author was affiliated with an African institution. This verification yielded an impressive accuracy of 98.4%, signifying that errors stemming from incorrect African authorship attribution were minimal. This higher accuracy compared to topic verification suggests that the primary source of initial false positives was indeed related to topic relevance rather than author affiliation.

Furthermore, to assess the consistency and reliability of our manual annotation, we calculated the inter-annotator agreement. We reported high agreement rates: 93.9% for topic verification and 96.7% for authorship verification. These high agreement scores underscore the clarity of our guidelines, the expertise of our annotators, and the overall robustness of our manual validation process, thereby strengthening the confidence in the quality of our refined dataset.

4. African Computer Vision Datasets

Despite commendable efforts from local communities to collect and promote high-quality data [36], African computer vision datasets face several intrinsic challenges, often related to scale, diversity, and accessibility. To comprehensively account for all contributions utilizing African data, our investigation explored both officially published datasets and unofficial ones. Our unique bottom-up approach yielded a substantial collection of 96 officially published datasets and 33 unofficial datasets, the latter primarily hosted on data hosting and data science competition platforms.

4.1. Dataset Taxonomy and Key Categories

Our analysis led to the development of a detailed taxonomy comprising 31 categories for the retrieved datasets, as visually represented in Figure 2 of the original PDF. This taxonomy distinctly highlights the variability of research topics within African computer vision, consistently demonstrating a strong emphasis on applications that directly benefit African communities. The taxonomy categorizes datasets with respect to both their applications (e.g., "remote sensing," "wildlife related") and the computer vision tasks they address (e.g., "object detection," "image segmentation").

Within the applications branch, we identified 19 distinct categories. Notably, categories such as "forests, plants, and agriculture related" (18 datasets), "document analysis and understanding" (17 datasets), and "animals, wildlife related" (8 datasets) emerged as highly prominent. These categories underscore the direct positive impact that computer vision research aims to achieve on the continent, addressing crucial sectors like food security, cultural preservation, and biodiversity monitoring. The category "Computer Vision for Social Good" also garnered significant attention with 13 datasets, reinforcing the problem-driven nature of research.

On the tasks side, 12 categories were identified. The most frequently represented tasks were general computer vision problems: "image classification" (60 datasets) and "object detection" (36 datasets). This indicates a foundational strength in these core CV capabilities. Following these, datasets related to "Humans: face, body, pose, gestures or movement" were significant (22 datasets), reflecting interest in human-computer interaction, biometric applications, and behavioral analysis. "Image segmentation" was also a substantial category with 14 datasets.

This granular taxonomy not only provides a structured overview of the types of datasets available but also offers insights into the prevailing research directions and the immediate needs being addressed by African CV researchers.

4.2. Overview of Officially Published and Unofficial Datasets

To provide a concrete illustration of the datasets cataloged, Tables 1 and 2 (from the original PDF) present ten representative entries each for officially published and unofficial African computer vision datasets, respectively.

Officially Published Datasets: These datasets include at least one author affiliated with an African institution.

- Ego4D Dataset [20]: This extensive collection of egocentric videos was gathered from approximately 74 worldwide locations, including Africa. Its inclusion highlights international collaborations and opens significant opportunities for advancements in robotics and augmented reality applications relevant to African contexts.
- ZeroWaste Dataset [6]: Designed for automatic waste detection, this challenging dataset features industrial-grade waste detection and segmentation scenarios, offering complex challenges for algorithms.

While the data itself was collected in the United States, its utility extends to efficient waste management strategies, a critical need across many African cities.

- Hausa Visual Genome [2]: This dataset is specifically designed for multi-modal machine translation from English to Hausa, incorporating image captions. The Hausa language is spoken in around eight African countries, making this dataset pivotal for developing language-sensitive CV applications and promoting linguistic diversity in AI.
- Predicting COVID-19 [32]: A dataset for deep learning models focused on predicting COVID-19 from chest X-ray images, directly addressing a critical public health challenge.
- Avo-AirDB [4]: An avocado UAV database used for agricultural image segmentation and classification in Morocco, showcasing the application of CV in precision agriculture.
- Land cover map of Vavatenina region (Madagascar) [25]: Produced by object-based analysis of very high spatial resolution satellite images, vital for environmental monitoring and land use planning.
- Scanned Arabic Books [16]: A large-scale benchmark dataset for extracting text from scanned Arabic books, critical for digitalizing cultural heritage and improving access to knowledge.
- Malaria and Sickle Cells Detection in Blood Films [26]: A dataset for weakly supervised deep learning to detect these diseases, emphasizing health diagnostics in low-resource settings.
- Photographed Lightning Events SA [22]: A dataset of lightning events in Johannesburg, South Africa, relevant for climate monitoring and infrastructure protection.
- Effects of Land cover change on Great Apes distribution in South East Cameroon [51]: A dataset for analyzing land cover change impacts on wildlife, crucial for conservation efforts.

The diversity of these officially published datasets—spanning COVID prediction, malaria detection, agricultural monitoring via UAV imagery, scanned book analysis for Arabic languages, land cover mapping, and weather monitoring—underscores the breadth of benefits these applications offer to African communities. Furthermore, we identified that many African datasets are published in venues like Data in Brief. While not always high-impact journals, these platforms are valuable sources for smaller-scale projects and challenges within Africa, making data more accessible.

Unofficial African Datasets: These datasets, often from data science competitions, are not formally published in academic papers but are widely used.

- Pothole Images of South African streets [Table 2, entry 1]: This dataset facilitates the development of automated road inspection systems.
- Nigeria Food AI Dataset [Table 2, entry 2]: Comprising images of 14 distinct indigenous Nigerian dishes, this is crucial for food recognition and dietary applications.
- Kenya Crop Type Detection [Table 2, entry 3]: Images of crop fields for agricultural monitoring.
- Spot the Mask Challenge [Table 2, entry 4]: Images of people wearing masks, relevant for public health and safety applications.
- Road Segment Identification [Table 2, entry 5]: Images of landscapes with or without road segments, useful for mapping and navigation.
- Local Ocean Conservation Sea Turtle Face Detection [Table 2, entry 6]: Images of sea turtles, vital for wildlife conservation efforts.
- Bill Classification in Tunisia Challenge [Table 2, entry 7]: Images of receipts from various sources, useful for financial automation.
- Computer Vision for License Plate Recognition Challenge [Table 2, entry 8]: Images of vehicle license plates for security and traffic management.
- Digital Africa Plantation Counting Challenge [Table 2, entry 9]: Images containing palm trees, aiding in agricultural surveys.
- Task Mate Kenyan Sign Language Classification Challenge [Table 2, entry 10]: Images depicting Kenyan sign language gestures, promoting inclusivity and accessibility.

These unofficial datasets, frequently found on platforms like Zindi (Africa's leading data science competition platform), indicate a vibrant, community-driven effort to generate and utilize data. Kenya, in particular, stands out as a significant contributor to these unofficial datasets.

4.3. Most Cited Datasets and Funding Initiatives

To further highlight impactful datasets originating from African institutions, Table 3 (from the original PDF) lists the top-5 most cited datasets based on both Scopus and Google Scholar. The consistent appearance of "Ego4D" [20] and "11K Hands" [3] on both lists underscores their significant impact and broader recognition within the global CV community. "Oil Palm Ghana" [11] and "Traffic Signs Detection" [5] also feature prominently, demonstrating the practical relevance and academic influence of African-centric research.

Crucially, fostering the creation and acquisition of African datasets requires sustained financial and institutional support. Table 4 (from the original PDF) provides a list of key funding agencies and programs that actively support African research and dataset acquisition. These include:

- AfriLabs and Code for Africa: Support innovation hubs and technology for social justice.

- The Engine Room and The Africa Data Hub (ADH): Focus on data-driven solutions and open data initiatives.
- African Union Development Agency (AUDA-NEPAD) and African Development Bank (AfDB): Promote broader economic development through data and technology.
- Open Data Portal and Lacuna Fund: Specifically encourage the creation and availability of datasets for research.
- Zindi: Beyond hosting challenges, Zindi also facilitates data collection efforts.
- Partnership for African Social and Governance Research (PASGR) and DataFirst: Support data infrastructure and research.
- DS-I Africa Program (NIH, United States) and Horizon Europe (European Commission): Represent international funding bodies with programs dedicated to bridging productivity gaps, particularly in Sub-Saharan Africa [47].

These initiatives are vital in addressing the resource disparities that African researchers often face, facilitating the creation of locally relevant datasets that are critical for developing effective and equitable computer vision solutions.

5. African Computer Vision Topics

This section delves into the specific research topics and recurring keywords that characterize the computer vision field in Africa, using the comprehensive "full set" of publications for this analysis. We primarily relied on this full set rather than the "refined set," as the latter's dependence on the top-50 global computer vision keywords in its query generation could potentially skew results and underrepresent topics unique to the African research landscape. The keywords for each publication were retrieved using the off-the-shelf SciVal tool [SciVal], which applies a standard clustering procedure to identify prominent themes.

From an initial pool of 187,812 keywords, we identified the top-30 most recurring ones. To ensure a fine-grained analysis of specialized topics within computer vision, we intentionally excluded four broad keywords from this top-30 list: "Computer Vision," "Camera," "Convolutional Neural Networks," and "Deep Learning." These terms, while fundamental to the field, are too general to provide specific insights into unique research foci. The remaining 26 keywords were then manually categorized to construct a taxonomy of the most researched computer vision topics across the continent.

5.1. Taxonomy of Research Topics

Our manual categorization process led to the identification of several key topic categories, along with their associated keywords, as illustrated in Figure 3 of the original PDF. These categories provide a comprehensive overview of the prevalent research interests:

- Photogrammetry and Remote Sensing: Keywords: Remote Sensing, Landsat, Hyperspectral Imagery, Land Cover. This category highlights a strong focus on environmental monitoring, resource management, and geographic information systems (GIS), which are critical for many African nations.
- Medical and Biological Vision: Keywords: Radiological Findings, Clinical Features, Mammography, Breast Neoplasms, COVID-19, Cancer, Case Report, Magnetic Resonance Imaging, Nanocrystal. This broad category underscores the significant application of CV in healthcare, from diagnostics for prevalent diseases like COVID-19 and cancer to advanced medical imaging techniques.
- Forests, Plants, Agriculture related: Keywords: Crops. This reinforces the importance of CV in agricultural productivity and natural resource management.
- Animals, Wildlife related: Keywords: Animals. This signifies research contributions to biodiversity conservation and wildlife monitoring, often through image and video analysis.
- Galaxies Morphology related: Keywords: Galaxies. This was a surprising emergence, indicating research in astrophysics and astronomical image analysis.
- Image Encryption: Keywords: Steganography, Hyper-chaotic Systems, Cryptography. This category highlights research in image security and data protection.
- Texture Analysis: Keywords: Crystalline Texture. This points to fundamental research in image processing and material analysis.
- Biometrics: Keywords: Biometrics. Reflects work on identification and verification systems.
- Video: Action and Event Understanding: Keywords: Video recording. Covers analysis of dynamic visual data.
- Object Detection: Keywords: Object Detection. A core CV task with broad applications.
- Image Segmentation: Keywords: IOU (Intersection Over Union). Another fundamental CV task crucial for precise object delineation.

Interestingly, three topics — "Galaxies Morphology related," "Texture Analysis," and "Image Encryption" — emerged during this keyword analysis that were not as prominent in our initial dataset categorization. To verify the relevance of surprising keywords like "Galaxies" and "Crystalline Texture," we randomly inspected five publications for each. We confirmed that "Crystalline Texture" was consistently used in publications related to texture analysis and classification, which falls within computer vision. For "Galaxies," while some publications were indeed relevant to computer vision (e.g., [18]), others were not (e.g., [42]). This indicates a nuanced overlap with broader scientific fields.

5.2. Regional Distribution of Research Topics

The distribution of these top-30 keywords across the different African regions provides critical insights into specialized research strengths and prevailing interests, as depicted in Figure 4 (A-E) of the original PDF. It is important to note that a single publication may contribute to multiple regions if its authors are from different African countries.

- Northern Africa (Figure 4A): This region shows a significantly higher contribution to "Image Segmentation," with approximately 90% of publications related to this topic originating from Northern Africa. "Object Detection" also features prominently. This suggests a strong focus on precise image analysis and object recognition techniques.

- Southern Africa (Figure 4B): Intriguingly, "Galaxies" research is predominantly concentrated in Southern Africa. While initially perplexing, this could be linked to significant astronomical initiatives in the region, such as the Square Kilometre Array (SKA) project, which would naturally generate large volumes of image data requiring CV analysis.

- Eastern and Western Africa (Figure 4C, D): Both regions show notable research activity in "Landsat" and "Land Cover," positioning them as the second or third most active regions in these areas, though Northern and Southern Africa often dominate. This highlights ongoing efforts in remote sensing and environmental monitoring across these regions.

- Central Africa (Figure 4E): Compared to other regions, Central Africa appears to have the least representation across the identified top keywords, suggesting a greater need for capacity building and investment in computer vision research in this area.

The distribution of topics per region raises an important question: do these research priorities align with the most urgent needs of the respective African communities? While this study does not definitively answer this, the presented regional topic distribution serves as a vital enabler for researchers, policymakers, and funding bodies to make informed decisions and strategically direct future research efforts to maximize societal impact.

Finally, we analyzed the citations of publications within the refined set across different regions. The top-cited papers per region provide further insights into influential research:

- North Africa: Sentiment analysis algorithms and applications: A survey [28]

- Southern Africa: scikit-image: image processing in python [48]

- Eastern Africa: Soil-grids1km—global soil information based on automated mapping [22]

- Western Africa: Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges [34]

- Central Africa: Quantifying forest cover loss in democratic republic of the congo, 2000–2010, with landsat etm+ data [38]

These top-cited works reflect diverse research strengths, from foundational image processing libraries to applied solutions in health, environmental monitoring, and human activity recognition, demonstrating the breadth and impact of African contributions.

6. Publishing and Collaboration Trends

Understanding the publishing patterns and collaboration dynamics within African computer vision research is crucial for assessing the field's growth, identifying disparities, and formulating strategies for future development. Our analysis examined these trends across different African regions and in relation to global contexts.

6.1. Geo-Temporal Publishing Patterns

Figure 5 (from the original PDF) illustrates the number of Scopus-indexed computer vision publications originating from different African regions over the ten-year period from 2012 to 2022, using a logarithmic scale to highlight growth trends. The data is based on publications from the refined set that included at least one author affiliated with an African institution.

The figure clearly demonstrates that Northern Africa and Southern Africa are the two leading regions in terms of computer vision publication output. Cumulatively, these two regions account for approximately 88.5% of the total publications in the refined set. Both regions exhibit consistent growth in their publication numbers throughout the analyzed period. This dominance suggests more established research infrastructure, greater access to resources, and possibly longer-standing research traditions in these parts of the continent.

While Northern and Southern Africa lead, Eastern Africa and Western Africa show a consistent and encouraging growth trajectory in their publication output, particularly over the period from 2016 to 2022. This upward trend indicates burgeoning research activity and increasing capacity in these regions. In contrast, Central Africa appears to lag significantly, demonstrating the lowest number of publications. This highlights a critical need for substantial investment and capacity-building initiatives in Central Africa to improve its computer vision research ecosystem. Addressing this disparity is vital for achieving more equitable development across the continent.

6.2. Contributions to Top-Tier Venues

To gauge African researchers' engagement and impact within the global elite of computer vision and machine learning, we analyzed their contributions to top-tier venues (CVPR, ICCV, ECCV, ICML, NeurIPS, ICLR, MICCAI, TPAMI, IJCV). Figure 6 (from the original PDF) presents the number of "publication-researcher pairs" across all continents over the past decade (2012-2022). We specifically use "publication-researcher pairs" to provide a fairer representation of the number of individual researchers from African institutions contributing to these leading platforms.

The figure strikingly illustrates the pronounced global imbalance in top-tier publications. North America and Asia overwhelmingly dominate, collectively accounting for approximately 74% of all publication-researcher pairs in these premier venues. In stark contrast, Africa's contribution stands at a mere 0.06% of the total publication-researcher pairs. Furthermore, unlike other continents that show consistent growth, Africa's representation in top-tier venues does not exhibit a sustained increase over the years. This quantitative evidence unequivocally documents the inequity in research opportunities and access faced by African researchers. Access to top-tier publications is not merely about prestige; it is a vital gateway to scholarships, substantial research grants, and crucial international collaborations, all of which directly impact the availability of high-quality datasets and advanced computational resources for African researchers. This disparity underscores a significant structural barrier that requires urgent attention. Additional granular analysis of these numbers per year and continent can be found in our code repository [8].

6.3. Collaboration Patterns

Figure 7 (from the original PDF) provides a critical analysis of collaboration patterns in African computer vision publications, distinguishing between intra-African collaborations (collaborations solely among African researchers/institutions) and international collaborations (collaborations involving African researchers and partners outside Africa) over the past ten years.

The data reveals a stark reality: international collaborations overwhelmingly dominate African computer vision research. Publications resulting from international partnerships far outnumber those from collaborations confined to the African continent. In fact, intra-African collaborations constitute a very minimal amount, forming only 3.9% of the total publications analyzed.

This finding carries significant implications. While international collaborations undoubtedly bring valuable resources, expertise, and exposure to African researchers, a heavy reliance on them can also perpetuate existing power imbalances and potentially lead to research agendas that are not always optimally aligned with pressing local needs. We strongly believe that encouraging and strengthening collaborations among African researchers and institutions is paramount for bolstering the continent's research ecosystem. African countries frequently share common problems, challenges, and developmental bottlenecks. By fostering robust internal networks, researchers can collectively develop context-specific solutions, share limited resources more efficiently, build independent research capacity, and reduce dependency on external entities. This internal synergy can ultimately contribute to greater data sovereignty and the development of AI algorithms that are truly beneficial for African economies and societies. Moreover, as will be discussed in the next section, a large-scale questionnaire among African researchers widely concurs that strengthening local collaborations is one of the most urgent priorities for improving the research ecosystem in Africa.

7. Large-scale Questionnaire: African Researchers' Perspectives

To gain a nuanced, on-the-ground understanding of the computer vision field in Africa, we conducted a large-scale questionnaire surveying African researchers about their perceptions of the field, the barriers they encounter, and their priorities for improvement. This builds upon a pilot study [37] which involved 14 community members from Egypt, Nigeria, Cameroon, and Benin, exploring barriers facing African computer vision researchers. The insights from this pilot study were instrumental in refining the questions for our larger survey.

We disseminated our large-scale survey through the Deep Learning Indaba platform, a prominent initiative for AI education and community building in Africa. This yielded 115 responses from researchers across the continent, providing a robust sample of perspectives. The majority of participants were graduate students (44%), followed by undergraduate students (28%), with faculty and industry professionals also contributing.

7.1. Participant Demographics

Figure 8 (from the original PDF) illustrates the regional distribution of our questionnaire participants, distinguishing between their region of citizenship (left) and region of residence (right). This distinction is crucial for understanding whether participants are actively engaged in the research ecosystem within Africa or if they have migrated for opportunities abroad.

- The highest participation came from Eastern Africa (50.4%), followed by Western Africa (31.2%). This aligns somewhat with the growth trends observed in publishing output from these regions.
- Southern Africa had the lowest participation, which could indicate challenges in reaching researchers in this region or a smaller overall community participating in such surveys.
- Crucially, the figure demonstrates that the vast majority of participants were not only African citizens but

also resided in Africa. This ensures that the insights gathered accurately reflect the perspectives of those directly immersed in and contributing to the continent's research ecosystem.

7.2. Perceived Barriers and Urgent Directions

The questionnaire focused on two core questions to elicit direct feedback from the researchers:

(i) "What can you identify as Top-3 setbacks/structural barriers in African computer vision research? Select from the list and/or add more under Others."

(ii) "What do you think is the Top-2 urgent directions to improve the computer vision research eco-system in Africa? Select from the list and/or add more under Others."

For the first question regarding structural barriers, participants were provided with options such as 'lack of funding' and 'poor economic systems.' The former directly impacts the ability of research labs to conduct experiments and sustain operations, while the latter can lead to a "brain drain," where talented individuals leave the continent in search of better economic prospects and more robust research infrastructure. Our findings revealed that the top three barriers identified by the participants were:

1. Lack of funding: This was consistently cited as the most significant hurdle, impacting everything from equipment acquisition to researcher salaries and project sustainability.

2. Low access to resources (e.g., compute): Limited access to high-performance computing resources, essential for deep learning and large-scale CV tasks, was another major concern.

3. Limited availability of African datasets: The scarcity of diverse and context-specific datasets relevant to African realities was frequently highlighted, underscoring the challenges of building localized AI solutions.

For the second question concerning urgent directions for improvement, the consensus among participants pointed to two key priorities:

1. Establishing research collaborations across African universities/research institutes: This was strongly favored, reinforcing the need for internal networks and shared knowledge.

2. Launching projects to curate African computer vision datasets: This aligns with the identified barrier of data scarcity and highlights a proactive approach to building foundational resources.

7.3. Fine-Grained Regional and Career Position Analysis

A fine-grained analysis of the responses based on regional representation and career position provided deeper insights into the varying perspectives across the continent and within the research hierarchy. Participants were allowed to choose multiple answers, and percentages were computed relative to the total participation per region or position.

Regional Distribution of Responses (Figure 9 in original PDF):

- Eastern Africa: Researchers from this region most strongly emphasized "Barrier 1: Lack of funding" and "Direction 1: Better computer vision courses taught in universities." This suggests a perceived need for both financial support and improved foundational education.
- Southern Africa: Participants from Southern Africa more consistently agreed on "Barrier 3: Low access to resources" and "Direction 4: Launching projects to curate African computer vision datasets." This indicates a primary concern with practical infrastructure and the foundational data needed for research.
- Differences were also observed for other regions, with varying degrees of emphasis on economic systems, lack of incentives, and teaching loads. These regional variations highlight the need for tailored interventions rather than one-size-fits-all solutions.

Career Position Distribution of Responses (Figure 10 in original PDF):

- Graduate Students: A significant majority of graduate students (54.5%) strongly supported "Direction 1: Better computer vision courses taught in universities." This is understandable, as they are often at the initial stages of their academic careers and highly value structured learning.
- Industry Professionals: In contrast, industry professionals showed less agreement (21.4%) with the need for better university courses. Their priorities leaned towards "Direction 2: Research collaborations across African universities" and "Direction 4: Launching projects to curate African datasets." This reflects a more practical, application-driven perspective, valuing collaborative research and data availability for real-world problem-solving.
- Faculty perspectives generally aligned with the overall consensus on funding and resources, while also emphasizing the importance of collaborative research.

The collected responses from this large-scale questionnaire strongly corroborate the recommendation [37] that a balanced approach, fostering both internal (intra-African) and external (international) collaborations, is essential for addressing these persistent barriers. Furthermore, the findings suggest that the progressive dissemination of cutting-edge computer vision techniques through local training initiatives and regional competitions could significantly promote technical expertise and ensure the availability of diverse datasets. We firmly believe that strengthening African collaborations at the university level and continuously improving computer vision curricula are crucial directions to pursue for sustainable growth.

8. Conclusion and Future Directions

The landscape of computer vision research in Africa is demonstrably dynamic, resilient, and inherently purposeful. It actively contributes not only to the resolution of critical local challenges but also profoundly enriches global conversations on the ethical, inclusive, and responsible development of Artificial Intelligence. While confronting inherent challenges related to data scarcity, infrastructure limitations, and historical underrepresentation in top-tier venues, researchers across the continent are consistently demonstrating remarkable innovation, adaptability, and a deep commitment to addressing context-specific needs.

The problem-driven nature of African CV research is a defining characteristic, leading to the development of solutions uniquely tailored to the continent's diverse socio-economic and environmental realities, particularly in areas such as agriculture, healthcare, and environmental monitoring. The proactive efforts to create and curate localized datasets, exemplified by initiatives like the Hausa Visual Genome and datasets addressing social issues, are pivotal in overcoming the biases and limitations of globally sourced data. Furthermore, the strong and articulate emphasis from African researchers on ethical AI, including the vital discourse on decolonization and the integration of indigenous philosophies like Ubuntu, offers invaluable contributions to shaping a globally equitable and humane AI future.

Our study has presented a comprehensive case study on African computer vision research, meticulously detailing the observed inequities both within the continent and in comparison to the global context of publications. We have provided detailed taxonomies for the various datasets available and the prevalent research topics being pursued across Africa. This catalog of datasets is intended to facilitate small-scale projects, encourage new research, and catalyze further efforts to curate computer vision datasets within the identified taxonomy of research topics. Moreover, our regional distribution analysis of the most recurring research topics serves as a crucial guide for researchers and policymakers, enabling them to make informed decisions regarding whether ongoing research truly aligns with the pressing needs of their respective communities. Finally, the insights garnered from our large-scale questionnaire unequivocally highlighted a consensus among participants regarding the key structural barriers they face, with a resounding emphasis on the urgent need for robust internal collaborations.

For our future work, building upon the foundations laid by this study, we aim to focus on several key initiatives:

- Establishment of an Academic Committee: We envision the formation of an academic committee dedicated to discussing, standardizing, and enhancing computer vision syllabi across African universities. This committee would also focus on the effective dissemination of cutting-edge knowledge through structured courses and specialized summer schools.

- Support for Educational Initiatives: Our research community has already contributed to the first African Computer Vision Summer School (ACVSS) (https://www.acvss.ai). We will continue to support and expand such initiatives. Similar valuable programs include the RISE-MICCAI Winter and Summer Schools (https://miccai.org/index.php/about-miccai/rise-miccai/) and the ACM SIGIR/SIGKDD African Summer School on Machine Learning for Data Mining and Search (https://sigir.org/afirm2020/). These programs are vital for providing high-quality computer vision and artificial intelligence training for African researchers, often offering full scholarships or affordable registration fees to maximize accessibility.

- Encouraging Data-Driven Projects: We intend to actively encourage and facilitate African research projects that leverage our meticulously compiled listing of datasets. This direct utilization of locally relevant data will be instrumental in further building and solidifying computer vision capacity across the continent.

- Broader Data Inclusion: Future work will explore methods to incorporate additional databases beyond Scopus, such as arXiv, and to include publications in other widely used African academic languages (e.g., French, Arabic, Swahili) to provide a more truly comprehensive and equitable view of the continent's research output.

In essence, continued strategic support, increased investment in local data and infrastructure, and the sustained fostering of collaborative initiatives—both within Africa and with aligned international partners—will be instrumental in unlocking the full transformative potential of computer vision to drive equitable and sustainable development across the African continent, further solidifying its critical role in the global AI landscape.

Limitations

While this study offers valuable and extensive insights into the field of computer vision research in Africa, it is essential to acknowledge its inherent limitations, which can guide future research methodologies.

One notable limitation is our primary reliance on Scopus as the sole data source. Although Scopus is a comprehensive database, it is disproportionately tied to venues that often involve high publishing costs. These costs can pose significant barriers for researchers in lower-income regions, particularly across Africa, where financial constraints may redirect researchers to alternative, more affordable publishing platforms not indexed by Scopus. Consequently, our findings might inadvertently underrepresent a segment of African research output.

Furthermore, Scopus is predominantly dominated by publications in the English language. This introduces a significant language bias, as a substantial body of academic research in Africa is published in other widely used languages, such as French (especially in West and Central Africa), Arabic (in North Africa), and even a growing number of local African languages. Our current dataset regrettably omits these crucial publications, leading to an incomplete representation of the continent's diverse research contributions. Future studies should endeavor to incorporate multi-lingual databases and employ advanced cross-lingual search strategies to capture this missing research.

Another limitation pertains to the accuracy and completeness of our data retrieval. While our search query — ("image" OR "computer vision") — was designed for broad coverage, determining its precise recall (the proportion of relevant papers found out of all relevant papers) is inherently challenging. It is plausible that our automatic analysis may have missed some pertinent papers or, conversely, retrieved some irrelevant ones that slipped past the verification filters. The broadness of keywords can sometimes lead to false positives where "image" or "vision" might be used in a context unrelated to computer vision (e.g., medical imaging reports without computational analysis). Exploring more sophisticated and context-aware search strategies, potentially involving natural language processing models trained on the specific nuances of scientific literature, could significantly improve the robustness and completeness of future analyses.

Finally, while we made concerted efforts to involve a diverse research team from various African regions, the sample size for our large-scale questionnaire (115 responses), while substantial, may not fully capture the complete spectrum of experiences and opinions across all sub-regions and diverse research communities within Africa. Future surveys could aim for even broader participation and employ stratified sampling techniques to ensure more proportional representation.

Despite these limitations, our study provides a foundational and detailed analysis, laying critical groundwork for more expansive and inclusive research into the dynamic field of computer vision in Africa.

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