Hindawi
Advances in Agriculture
Volume 2023, Article ID 1530629, 9 pages
https://doi.org/10.1155/2023/1530629

Research Article

Challenges of Computer Vision Adoption in the Kenyan Agricultural Sector and How to Solve Them: A General Perspective

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Received 21 September 2022; Revised 26 February 2023; Accepted 27 February 2023; Published 7 March 2023

Academic Editor: Xinqing Xiao

This study addresses the underlying challenges of computer vision adoption in the Kenyan agricultural sector and how to solve these hurdles to commercialize this technology. Technological advancements have revolutionized the agriculture sector, where artificial intelligence enhances yields, mitigates losses, and manages natural resources, leading to increased productivity. Kenya is still lagging in the commercialization of computer vision to improve its agricultural sector, which is the largest source of GDP. Kenya has remarkable skills and expertise in artificial intelligence that can support artificial intelligence implementation; the government policies, data availability, and high cost incurred in starting a computer vision company are problematic. Through better government policies on subsidies and data, research and development investments, and AI forums, Kenya will solve the challenges of adopting computer vision. While computer vision has the potential to revolutionize the agricultural industry by improving crop yield, detecting diseases, and increasing efficiency, there are several barriers to its adoption, including inadequate infrastructure, lack of technical expertise, and limited funding. This study aims to identify the challenges hindering the implementation of computer vision technology in the Kenyan agricultural sector and propose potential solutions to address these challenges.

1. Introduction

Improvements in computer storage capacity and processing speed, advancements in algorithmic techniques, and the increase in the availability of data have enabled the development of artificial intelligence (AI) technology. Machine learning (ML), a branch of AI, has shown a strong capacity and capabilities in simulating characteristics attributed to human intelligence that are not restricted to speech, vision, and problem-solving [1]. The most significant effects of AI will be felt in sectors that were not traditional users of this technology because of the efficiency and interoperability. In recent decades, computer vision research in image processing, pattern recognition, and classification has made substantial progress [2]. According to [2], computer vision has recently attracted increasing attention for conveniently improving production. Agriculture is a vital sector of the Kenyan economy and using computer vision to enhance yields, mitigate losses, and manage natural resources is crucial. In addition, AI usage in agriculture is advancing with more research on the feasibility of different AI technologies to help farmers reduce and eliminate manual labor, increase crop yield, and save money. Specifically, the global AI market is projected to grow from an estimated $1.0 billion in 20202 to $4.0 billion by 2026, representing a 25.5% increase [3]. This increase is attributed to the increasing implementation of sensors and deep learning technologies that collect area images for crops used for decision-making. Despite the high level of investments in terms of resources and technology, the Kenyan agricultural sector experiences several challenges that are preventing it from reaching its productive potential, which can be resolved in the near future.

1.1. Overall Objective. The objective of this study is to investigate the challenges facing the adoption of computer vision technology in the Kenyan agricultural sector and propose possible solutions to overcome these challenges.

1.2. Specific Objectives

(1) Identify the major challenges faced in the adoption of computer vision technology in the Kenyan agricultural sector

(2) Analyze the impact of these challenges on the effectiveness and efficiency of the agricultural sector in Kenya

(3) Propose feasible solutions and recommendations for addressing the identified challenges to improve the adoption of computer vision technology in the Kenyan agricultural sector

(4) Provide a general perspective on the potential benefits of computer vision technology adoption in the Kenyan agricultural sector, as well as the risks and limitations that need to be considered

2. Computer Vision: An Overview

2.1. A Historical Perspective of Computer Vision. Larry Roberts is considered the father of computer vision. His Ph.D. thesis at MIT discussed the possibility of extracting 3D geometric information from 2D perspective views of blocks [4]. The researcher then considered images from the real world for low-level vision tasks, including edge detection and segmentation [4].

In addition, the development of machine learning originated from the exploration of brain cell interaction modeling [5]. Neurons have excitement and communication to process and fire information to one another. These historical advancements led to the development of artificial neural networks (ANNs) to create perceptron [6]. More advances have led to the discovery of multilayer perceptron that can yield better results and accuracy. It is also evidenced that the advancements considered the growth in computer architecture to improve machine learning capabilities.

The most impactful computer vision advancements also attached to most ML research were evidenced in the backpropagation algorithm. This optimization algorithm considers space and time to allow the processing of large datasets in ANNs [6]. Backpropagation updates the parameters to conform to data patterns and minimize the cost function. In practice, backpropagation in ANNs updates the weights of neuronal connections by back-propagating the residuals between the actual and predicted values [6].

The idea of computer vision has been geared toward giving machines the power of visual recognition that can replicate human vision and intelligence. Computer vision aims to make decisions through image interpretation using algorithms. The growth in computer vision is attributed to the explosion in the volume of visual data, the increased sophistication of artificial neural networks, and the availability of chips specifically designed for artificial intelligence processes [2]. Currently, several computer vision algorithms are being developed for various applications to pursue faster learning processes, accuracy in the prediction, and usability on the available devices.

2.2. Computer Vision Techniques. Computer vision extracts meaningful information from images and videos in an automated way. Such an approach allows cameras and computers to unify and to do stuff that could otherwise require manual work. Computer vision represents a relative understanding of a visual environment involving cross-domain mastery, such as computer science, mathematics, engineering, biology, and psychology [2]. Recent developments in neural networks and deep learning have leveraged computer vision techniques. The three primary computer vision techniques include image classification, object detection, and image segmentation.

2.2.1. Image Classification. Image classification involves categorizing and labeling groups of pixels in an image. The choice of categorization is devised on the particular characteristics using supervised and unsupervised methods. Image classification solves problems including viewpoint variation, scale variation, intraclass variation, image deformation, image occlusion, background clatter, and illumination conditions [7]. Advances in computer vision research have led to a data-driven approach that classifies images into distinct categories. The approach works by providing a computer with a few examples of each image class and expanding the learning algorithms on the specific class. The algorithms look at the bar and learn about the visual appearance of each type. Specifically, convolutional neural networks (CNNs) are a famous classification architecture since network images can be fed in, and the network categorizes the data into classes [8].

2.2.2. Object Detection. Object detection locates instances of objects in videos or images. According to Brownlee, computer vision identifies objects within an image by outputting bounding boxes and labels for each item of interest [8]. While image classification focuses on a single dominant object, object detection uses classification and localization for many objects. Object detection uses object-bounding boxes and nonobject bounding boxes. For example, in vehicle detection, the algorithm identifies all vehicles with four wheels, three wheels, and two wheels using bounding boxes. CNN has been used in object detection because it classifies crops from each picture as backgrounds or objects and can deal with the winding number of rather expensive localizations.

2.2.3. Image Segmentation. Image segmentation partitions an image into multiple regions of pixels. Rather than detecting what classes you have in the image, semantic segmentation classifies all the pixels in the image to determine what type of object is contained [9]. In addition, instance segmentation classifies objects in the image at a pixel level and differentiates instances of a specific class. Another type of segmentation is panoptic segmentation. It is the most potent segmentation methodology since it combines semantic and instance segmentation [10]. It has the capability of pixel-level and instance-level classification.

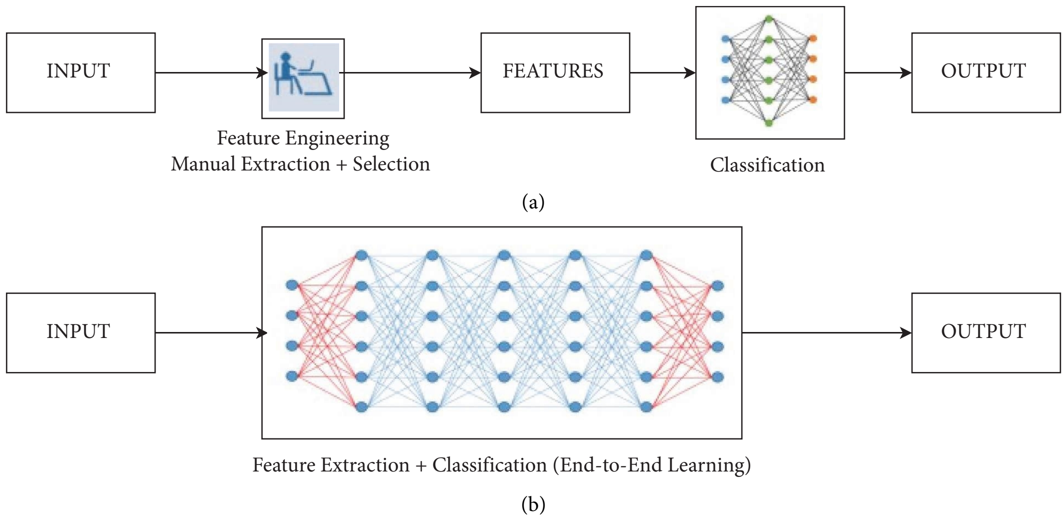

Figure 1: (a) Traditional image processing model and (b) deep learning model. Source: [7].

2.3. Computer Vision and Traditional Image Processing Approaches. Deep learning has led to the development of computer vision techniques. While traditional image processing techniques differ from deep learning techniques for computer visions, these approaches are imperative in understanding the aspect of image processing and interpretation. Deep learning techniques in computer vision have revolutionized traditional image processing owing to increased processing power. Deep learning has pushed the potential of artificial intelligence to open up opportunities in diverse industries. As opposed to conventional image processing, deep learning has achieved greater accuracy [7]. Figure 1 shows a comparison between the traditional image processing model and the deep learning model.

Deep learning and computer vision methodologies have rapidly advanced various aspects. Memory-hungry, high computing power, high power consumption, optics, and high image sensor resolution have accelerated the spread of computer-based applications with cost-effectiveness and improved performance [7]. Since the neural network used in computer vision is trained rather than programmed, the application for computer vision becomes easily scalable, requires less fine-tuning, and less expert analysis since there is no direct human involvement. Such a possibility has allowed the processing a humongous amount of video and image data in today's systems [7]. While computer vision algorithms are domain-specific, deep learning has provided flexibility since convolutional neural network models can be trained on custom datasets for any use case. Figure 2 shows a comparison between data and performance comparison.

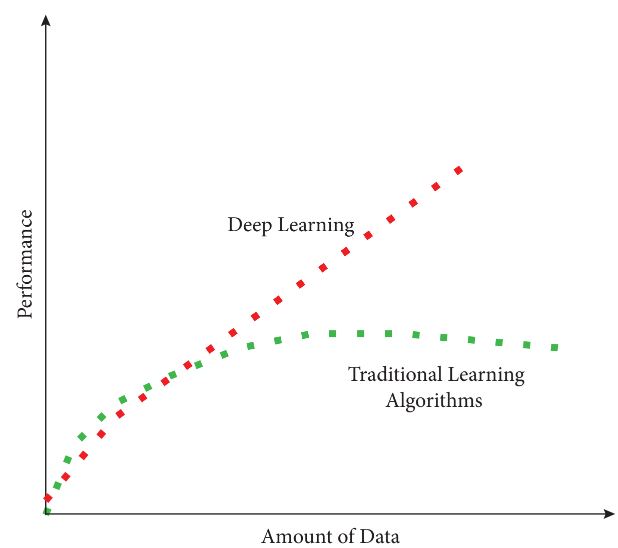

Figure 2: Data vs. performance comparison source [7].

Computer vision models can solve more complex cases, while traditional image processing can solve problems with greater accuracy at lower levels. Notably, the features learned from the computer vision neural network are specific to the training dataset [7]. When such neural networks are not constructed effectively, they may not perform well for images that were not used in the training process [7]. Some traditional computer vision algorithms, such as the scale-invariant feature transform (SIFT) or simple color thresholding and pixel counting algorithms, are not specific to any class and can perform in a general perspective [11].

Traditional image processing is preferred for simple tasks such as classifying items in a conveyer belt [11]. In this case, a simple color thresholding technique can be used to classify cans or boxes based on their color more accurately than deep-learning computer vision techniques. While deep-learning models can be considered as black boxes because of the manual tweaking of model parameters, it becomes difficult to do this, especially for millions of parameters [11]. Traditional image processing offers complete transparency since the model's behavior in a different environment is easy to predict. The parameters in the conventional models can be tweaked to improve accuracy and performance.

Hybrid image processing approaches amalgamate the best of deep learning and traditional image processing

Table 1: Traditional vs. computer vision comparison based on criteria.

Criteria	Traditional image processing	Computer vision
Dataset	Small	Large
Computational power	Low	High
Training time	Short	Long
Feature engineering	Needed	Not necessary
Annotation time	Short	Long
Domain expertise	High	Low
Deployment flexibility	High	Low

techniques [12]. The technique has been used to automate medical image processing and other industrial applications with reduced human error. Another example is the detection of faces from the live feed from a security camera, which is then relayed to a DNN as the next stage in face recognition [12]. The hybrid approach reduces computing resources and training effort and improves accuracy [13].

Making a suitable algorithm choice for image processing depends on data quality. According to [13], computer vision algorithms are powerful yet may not be ideal for every situation, such as in augmented or virtual reality or 3D modeling. In addition, Wang et al. mentioned that such algorithms might also not be fit for video stabilization, motion capture/calculation, noise reduction, image registration, stereo processing, and data compression and coding [14]. Computer vision algorithms aim to solve classification problems to map potential signals to a finite number of classes or categories. Deep learning needs to be combined with traditional image processing to solve the issues of priors such as smoothness, silhouette, and illumination information [13].

Tables 1 and 2 provides a comparison between traditional and computer vision comparison based on criteria as well as based on applications of traditional image processing and computer vision techniques.

2.4. Computer Vision Driving Force. The motive for integrating computer vision in artificial intelligence is to create a visual perception model that can be visualized without human intervention to make decisions. Visual perception involves acquiring data, processing, analyzing, and making decisions [15]. Machines can visualize scenarios through computer vision technology. The technology allows computer systems to precisely locate and identify videos and images to provide meaningful information.

In artificial intelligence, computer vision plays a significant role in training visual perception-based deep learning models to work in a real-life environment [15]. The accuracy and reliability of computer vision are based on high-quality training data to develop models [16]. Computer vision also provides artificial vision to machines to understand scenarios and make the right decisions [15]. Computer vision in AI is essential in developing machine learning models that can be used in different sectors, industries, and fields [15].

According to [15], as the Internet revolution tries to reduce the cost of information gathering, computer vision minimizes the cost of making predictions and enhances its utilization in various areas [15]. For example, engineers have long been designing autonomous cars in a well-controlled programming environment driven by computer vision and artificial intelligence. One of the driving forces in computer vision behind the transformation of many sectors suing or aspiring to use computer vision is the question, what would a human do with the technology to solve problems?

2.5. Computer Vision Use in the Agricultural Sector. Development theory has neglected the agricultural sector dominated by structural transformation and economic growth. The role of the industrial revolution was to transform peasants into industrial workers while ignoring the impact that agriculture could have on such a population [17]. For a long time, agriculture has been excluded as an aspect of the industrial revolution and is considered to have no significant impact on industrialization [18].

While industrialization was the ultimate engine for economic growth, the development of the agricultural sector created a long-term strategy that boosted economic growth. Nevertheless, the agricultural sector's reassessments have paved the way for research and technology to increase productivity [19]. This section will discuss how computer vision and machine learning can be harnessed to develop the agricultural sector in Kenya and Africa.

Over the past, the agricultural sector has been used to test technologies for the following reasons: the increasing population needs increased agricultural production for sustainability; advancements in technology that allow for increased automation in all sectors, including the agricultural sector; insufficient information on weather, market, and crop conditions to increase production; large employment opportunities in the agricultural sector; and the need to optimize agricultural operations [20, 21]. According to [20], these aspects have been addressed using digital tools, including mechanization, digital-enabled tools, biological engineering, satellites and drones, sensors, chemicals, and semiconductors. However, most of these tools and resources are not interoperable as a system, making them less effective in improving sustainable agricultural production.

Computer vision and machine learning technologies have spread faster in various sectors owing to advancements in research and development in artificial intelligence [22]. The impact of computer vision is felt in a different section of the food system in agriculture, not restricted to farm operations, planting periods, seed selection, control of pests and diseases, and harvesting [22].

The population project of the United Nations indicates that Africa will be a home of over 1.68 billion people by 2030, representing a significant increase of +42% compared to the population in 2015 [23]. The increasing population indicates that there is a need to increase food production. While food production can be the focus, sustainability matters to maintain consistency in the product over time.

Table 2: Applications of traditional image processing and computer vision techniques.

Computer vision	Traditional image processing
Image classification (OCR)	Image transformation (lens distortion correction)
Object detection	Image signal processing (ISP)
Sematic segmentation	Camera calibration
Instant segmentation	Defect detection
Scene understanding	Geometries calculation
Image colorization	Automatic panorama stitching
Image synthesis	Stereo image processing

Approximately 95% of Africans hold less than 5 hectares, making it difficult to extend the production and resulting in poor performance [23]. Other problems for low productivity in such small lands are erratic rainfall, soil water content, insufficient knowledge of biophysical variables, and inadequate planting periods. Computer vision and machine learning technologies can tackle these challenges to increase productivity and environmental sustainability [24].

2.6. Livestock Farming. Food security is one of the biggest challenges in Africa and the world. Livestock and poultry contribute 30% of the daily protein consumption from meat, milk, and eggs. Artificial intelligence is widely used in the livestock farming market in different parts of the world [25, 26]. According to [3], investment in computer vision is projected to increase by 2026. A report published by Global Market Estimates [3] demonstrates a compound annual growth rate (CAGR) of 25.6% during the forecast period of 2021–2016.

Computer vision embedded in the Internet of Things helps in monitoring the health of livestock, monitoring food supply, detecting abnormal behavior in animals, counting livestock through drones, and sending real time information about livestock to farmers for better management decision-making, animal welfare, disease detection, weight measurement, and egg examination for poultry. The study by [27] that conducted computer vision and deep learning system monitoring of cows demonstrated high accuracy with real-time data. The system could identify cows, evaluate their position and actions, and track their movement. Neural networks are used to analyze the video feeds from the camera in real time. Figure 3 shows the use of computer vision in livestock farming.

2.7. Improving Crop Yields. AI and computer vision models allow farmers to monitor crop growth near real time. For large tracks of land, satellite images provide a birds-eye view of the crop conditions that can be used to make decisions [9]. Drones have been used to collect images and video data that are then fed into models for analysis and crop monitoring [9]. Some parameters that can be analyzed based on the videos and images are general crop conditions, lack of moisture, crop diseases, and weed overgrowth. When these conditions are identified, a precision agriculture practice reduces physical labor, thus saving costs [28]. The models can also be used in predicting forthcoming yield based on the conditions that have been analyzed. In addition, computer vision can help yield prediction in fruits and vegetables with high accuracy, saving farmers from labor-intensive physical analysis [9].

2.8. Automating Produce Sorting. In most cases, agricultural produce is graded based on quality and size. Other variables include the product's color and physical appearance [29, 30]. In Africa, much sorting is done manually, such as discarding bad oranges or apples, which is tedious, time-consuming, and expensive. Computer vision solutions help identify defects and sort them based on weight, color, size, and ripeness, among other factors [31, 32]. The technology is also used to count fruits and vegetables more accurately and carefully.

2.9. Computer Vision Phenotyping. Plant phenotyping is the identification, measurement, and analysis of a plant's characteristics and environmental conditions to help in research and development [33]. The information is collected based on the ecological condition that specific plants can grow, how plants grow, and insight into plant genetics. With the effect of climate change globally, computer vision-enabled phenotyping allows farmers to learn more about plants and to make such plants more resilient to ever-changing weather and climate [34, 35]. Farmers will also know the best crops that would be successful and sustainable given a specific environmental condition.

3. Computer Vision Growing Interest in Kenya and Adoption Barriers

3.1. Artificial Intelligence Interest in Africa. There is a growing interest in artificial intelligence in Kenya and Africa. Start-ups are incorporating artificial intelligence in various industries [36]. AI start-ups use machine learning techniques that have proven to drive their business. In Africa, South Africa is the largest investor in AI, followed by Nigeria, Tunisia, Egypt, and Kenya [37]. These AI investments are based on technology firms that acquire promising start-ups. Briter [38] provides an overview of the African companies using Artificial Intelligence in Africa—Q3 2019. Based on [38], Kenya has the potential for involvement in artificial intelligence among African countries. There is a growing interest in AI and computer vision in Kenya, even though there is a lack of records documenting all the companies using this technology from various sectors. Some start-ups use data and analytics, Hub and AI centers,

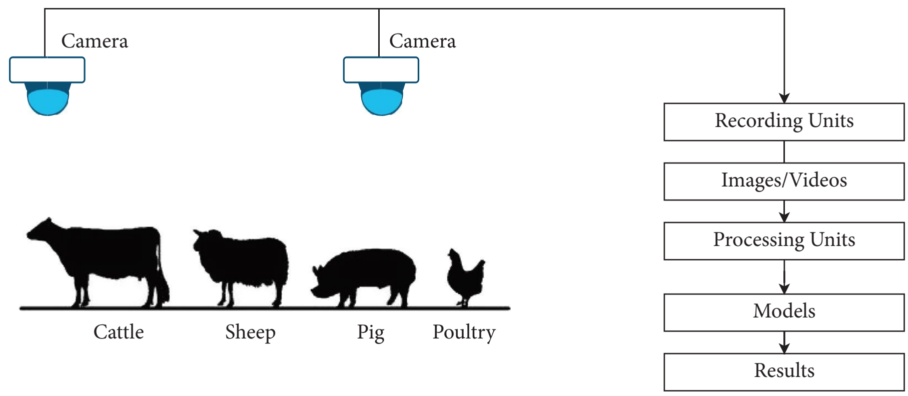

Figure 3: Computer vision in livestock farming source [27].

and health and diagnosis [38]. While there is no reporting on computer vision, there is evidence of computer vision start-ups developing in Kenya.

According to the research paper on AI adoption in Africa by [36], AI can be used to solve the most pressing issues in Kenya and Africa at large. More interest in using AI is placed on agriculture since it is the primary source of income, with the highest revenue for Kenyans [36]. The increasing number of start-ups in AI indicates growth in the GDP. There is a growing community of computer vision learners owing to the online courses in artificial intelligence and introduction to AI degrees in Kenyan universities. This indicates that there is the possibility of more developments of AI in the future that will solve the underlying problems in Kenya.

In addition, Kenya is also a hub for companies that use AI to solve business problems. Such companies are called machine learning enablers, including Google, IBM, and Microsoft. The presence of these companies is important since they bring awareness about the potential of AI in solving problems.

One of the reasons why Kenya may be lagging in terms of the adoption of AI and computer vision compared to other African countries is because of informal aspects. Kenya is not documenting many initiatives since they do not lead to company creation [39]. Like most African countries, Kenya is a developing country with an imperfect capital market, thus affecting entrepreneurial motives. In addition, there are high entry costs to the formal sector, which may affect the entrepreneurial space. Inappropriate government regulations are also a significant factor in entrepreneurship in the computer vision space in the Kenyan agricultural sector.

Despite the barriers to entry for computer vision companies and research and development in the agricultural sector in Kenya, such technologies can be applied in different ways to improve agricultural productivity. According to [40], agriculture is the backbone of the Kenyan economy, with more than 75% of the population depending on it, and it is among the leading in GDP. However, insufficient technology has contributed to slow and deteriorating production [41].

Computer vision can bridge the technological gap in agriculture by diagnosing soil defects and pests. Computer vision and deep learning allow farmers to identify nutrient deficiencies and soil defects. Such applications have been used in Germany and the United States, where image recognition apps are used to determine soil defects. Computer vision has also been effective in predicting weather forecast information. Images from satellites are analyzed using deep learning and machine learning algorithms to predict the weather for crop sustainability [41]. The drones also have precision sensors to conduct airborne surveillance and identify pests and diseases, weed damage, and student growth. Kenya can also use robots to harvest maize, team picking, and fruit picking, which will also converge in solving food security issues.

3.2. Potential Computer Vision Barriers in Kenya's Agricultural Sector. Insufficient data and lack of information about computer vision make it difficult to access its penetration in Kenya. Recently, more interest has been drawn to the topic, as evidenced by the increasing number of AI start-ups in Kenya [41].

We used Oxford Insights to understand the problems and understanding of AI R&D commercialization. Oxford Insights partnered with Cambridge Econometrics to develop a deep understanding of how AI research and development is transformed into marketable products and services [42]. The study explored barriers and challenges for AI commercialization, considering data from university spinouts, start-ups, big tech firms, and academic "founder-researchers." The research conducted 40 interviews across many industries and technology giants, such as Microsoft, Nvidia, BT Group, Siemens Digital, and DeepMind [42]. The research identified four significant findings that can be considered for our study [42].

(1) The value of AI is derived from its application and use in existing problems. The business needs to implement AI solutions to the issues at hand. Depending on data availability, there is also the need to commercialize AI research and development [42].

(2) AI commercialization requires commercial and sector-specific skills and technical AI skills. Academics and research founders develop specialized skills and technicalities in designing AI [42].

(3) Universities' equity share in their AI spinouts is a commercial barrier. Since universities are the locus of AI research and development, spinouts present a direct route by which research and development can be commercialized [42].

(4) There is a large flow of AI talent from universities to large tech companies [42]. Large companies have earning potential that attracts fresh graduates. Large companies also provide resources, including high computing power and large datasets with high precision, to AI models. In addition, there is high completion for AI talent, making it difficult for small businesses to recruit and retain such talent [42].

Based on the findings from Oxford Insights, Kenya has insufficient AI-driven companies to implement sophisticated computer vision research and development in agriculture. According to [39], the Kenyan government has invested in AI readiness more than any other African country, enabling Kenya to implement computer vision in solving agricultural problems. In Africa, only Kenya and Tunisia have a well-developed framework to enhance AI development among the 54 African countries [36]. Kenya also has high AI technological skills that can help in the commercialization of AI in agriculture; however, large technology companies such as Microsoft, Google, and IBM offer lucrative remuneration for graduates, making it difficult to start and develop start-ups [36]. Therefore, in terms of computer vision commercialization barriers in the agricultural sector, Kenya faces issues such as entrepreneurship, AI start-ups, private sector innovation technology, and technical skills, which need to be investigated. Kenya has only 8 AI firms in general and two in the agricultural sector [36]. Based on these findings, having a well-documented national AI strategy can set favorable entrepreneurship in AI in agriculture and general.

Another barrier to the commercialization of computer vision in agriculture is data availability. Machine learning models are generally data hungry, and a lack of data is undoubtedly problematic in developing precious models [36]. As Kenya is one of the largest agricultural hubs, data availability is not a problem. However, there is a thin line between data availability and data scarcity. The Kenyan government does not share the dataset with the public regarding crop and livestock diseases that can be used in computer vision. Kenya's government does not have a public repository to download such data, making the data scarce for public use. Even when such data could have been available, there is the need to incorporate academia to make them of high quality, giving correct implications when used in machine learning models.

There is also the need to collect ground truth data to make valuable predictions in the agricultural sector [36]. Entrepreneurs usually face the barrier of the high cost of sensors to gather data for agricultural AI models, which makes it difficult to make start-ups that can be relied upon. Sensors are needed to measure soil water content, humidity, temperature, wind speed, solar radiation, and image acquisition for image recognition [36]. While satellite images, drones, and remote sensing can be used to close the data gap in Kenya, highly specialized skills are needed to gather high-quality data. Thus, such barriers can compromise the commercialization of computer vision in agriculture.

3.3. Proposed Sector and Actions for Computer Vision Development in Kenya's Agricultural Sector

3.3.1. Start-Ups. The government of Kenya in 2018 announced the formation of a task force to work on a comprehensive strategy for adopting emerging technologies such as AI and blockchain. One of the strategies the government of Kenya should take to increase the enabling environment for computer vision is facilitating company creation by offering subsidies and tax relief that encourage companies to survive [43]. The Kenyan government should also incentivize AI products with tax exoneration.

3.3.2. Research and Development. In collaboration with the government, Kenya's education system should create attractive computer vision programs that are data-driven, especially those related to agriculture. There is also the need to fund research programs and support start-ups trying to solve agriculture-related problems using computer vision [43]. It is also important to sponsor doctoral programs to train more experts in the field of computer vision.

3.3.3. Data. There is a need to invest in confidentiality, availability, and integrity while dealing with data. Data are the backbone of the computer vision model; thus, choosing a public cloud system for data storage is vital [36]. Investment in technological tools such as sensors and drones to gather data will provide seamless data and be of high-quality [36]. The Kenyan government should create an agency that collects, annotates, and makes them publicly available for use while observing ethical standards on the use of data.

3.3.4. AI Forums. An AI forum is necessary because it will create awareness about the potential of all aspects of AI in the country. The forum will also share knowledge and data based on research and discussions with the experts. The forums can be organized locally or internationally and may involve showcasing innovations in AI for agriculture [44].

3.3.5. AI Use in Public Services. The Kenyan task force was to incorporate emerging technology into public services. Implementing this strategy will diffuse in other sectors, which is associated with increased efficiency in service delivery and the country's overall productivity [45].

4. Conclusion and Recommendation

This paper introduced artificial intelligence, including computer vision and machine learning, from a historical, technical, and general perspective. The paper also introduced the differences in the potential of deep learning in machine vision compared with traditional image processing techniques. It then highlighted the driving forces of computer vision that can facilitate the commercialization of this technology in the agricultural sector of the Kenyan economy. We also discussed the interest in computer vision adoption in the Kenyan agricultural sector and the potential barriers that can hinder such adoption. Nevertheless, some recommendations could be considered to ensure the effective commercialization of computer vision techniques in the Kenyan agricultural sector to improve productivity.

The private sector dominates the artificial intelligence and computer vision solutions in Kenya, leaving no or few opportunities for start-ups to dominate this market. This approach needs to incorporate a bottom-up approach that would give the start-ups a conducive environment and resources needed to scale up. The government should set up short-term and long-term policies and a thought framework to see small firms grow and solve the agriculture problems in the country. One of the policies should be protecting individuals and businesses by building a conducive environment for the operation. Another policy is to provide incentives and tax relief to allow such investors to bypass financial problems because computer vision resources are expensive. The government should also invest in education, research, and development to mentor the necessary and important skills in computer vision. There is also the need to create a public data repository to make local data available for research and development in agriculture. Moreover, knowledge sharing through discussion, research, and publications is essential when AI forums are given priority in Kenya to improve understanding in the field of computer vision.

4.1. Limitations of Using Computer Vision in Agriculture in Kenya. The use of computer vision technology in the Kenyan agricultural sector is not without limitations, particularly in relation to traditional or indigenous knowledge that has been passed down through generations and forms the basis of many farming practices. Some of the limitations include the following:

(1) Cultural barriers: Some farmers may not be receptive to the idea of adopting computer vision technology in their farming practices due to cultural beliefs or practices that are deeply ingrained in their communities.

(2) Technical knowledge: The use of computer vision technology requires technical knowledge and skills that may not be readily available among farmers or local communities in Kenyan rural areas.

(3) Infrastructure: The effective use of computer vision technology requires a reliable power supply, Internet connectivity, and other infrastructure, which may not be available in some rural areas in Kenya [42].

(4) Cost: The cost of acquiring and maintaining computer vision technology can be high, which may be a barrier to adoption for small-scale farmers who may not have the financial resources to invest in the technology.

(5) Potential disregard for indigenous knowledge: The adoption of computer vision technology in the Kenyan agricultural sector may lead to a disregard for indigenous knowledge and practices that have been developed over time and have proven to be effective in local farming conditions [42].

Data Availability

The data were taken from secondary sources of the references provided. Oxford Insights was the main case study for comparison and is also included in the sources in the link https://www.gov.uk/government/news/understanding-the-uk-artificial-intelligence-commercialisation.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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