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Leveraging Machine Learning for Crop Disease Detection and Prediction in African (Nigerian) Agriculture

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Abstract – This study investigates the use of machine learning (ML) techniques for detecting and predicting crop diseases in Nigerian agriculture. With agriculture playing a vital role in Nigeria's economy and crop diseases posing significant challenges, the research assesses the effectiveness of various ML algorithms in reducing losses through early detection. It explores data collection methods, the modeling process, and the transformative potential of integrating ML systems into agricultural practices across Africa. The findings demonstrate the high accuracy achieved by machine learning algorithms, underscoring their feasibility for widespread implementation.

Keywords – Machine learning, 5G technology, disease detection, disease prediction.

I. Introduction

Agriculture is a cornerstone of Nigeria's economy, employing about 70% of the population and contributing nearly 24% to the GDP. Effective tools for diagnosing crop diseases and disseminating agricultural information are essential for growth and development in the sector. Crop pests and diseases pose a significant threat, with annual yield losses of 35–40% reported in the sub-Saharan region [1]. Traditionally, disease detection has relied on agricultural experts. However, there is a notable shift toward using machine learning and computer vision techniques for crop inspection, facilitated by mobile devices [2][3].

For rural and smallholder farmers, mobile phones serve as vital tools for accessing information, markets, and services. Conventional methods of disease detection, which depend heavily on manual observation, are both time-consuming and error-prone. Disease management in Nigerian agriculture typically involves manual inspection and chemical treatments. While somewhat effective, these methods are labor-intensive, reactive, and lack a preventive approach.

The information needs of farmers are constantly evolving and can be understood as part of an agricultural cycle across different seasons [4]. Farmers frequently seek insights about their farms or gardens and often rely on advice from agricultural experts [5]. In cases where this process has been automated, feedback is typically delayed [6]. For instance, some diagnostic applications take approximately 5–7 days to provide farmers with feedback [7]. The lack of real-time information has contributed to poor farming practices among smallholder farmers, resulting in significant yield losses. Annually, crop diseases and pests cause yield losses of 20–40%, further intensifying food insecurity and poverty.

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This study explores the application of machine learning (ML) to provide real-time diagnosis and assessment of crop diseases directly in the field, empowering non-experts to take timely actions. It examines how ML techniques can transform disease detection and prediction by enabling early interventions and reducing losses.

2. Research Methodology

This study adheres to the PRISMA guidelines, an evidence-based framework for conducting systematic reviews. The focus is exclusively on the application of machine learning in farming. The search timeframe spanned from 2016 to 2024, with any articles outside this scope or unrelated to the research focus excluded. Following the PRISMA methodology, a systematic literature search was performed using digital journal databases such as ResearchGate, Google Scholar, and IEEE Xplore.

After screening, a selection of research publications and articles meeting the eligibility criteria was included for qualitative analysis. These articles were meticulously reviewed to gather key insights on the impact of IoT, Big Data Analytics, and Machine Learning on farming in Africa, with a particular emphasis on Nigeria. The reviewed literature was compared based on the advantages, disadvantages, and applications of these technologies in the agricultural sector.

3. A review of Machine Learning Models and application in farming

Machine learning, a critical branch of artificial intelligence, focuses on developing and optimizing algorithms and statistical models that enable computers to perform tasks autonomously without explicit programming [8]. Instead, these systems identify patterns and make predictions or decisions based on input data. Several machine learning approaches facilitate efficient model training [9]:

1. Supervised Learning: This method uses training datasets comprising input-output pairs, where each input is associated with a known output.
2. Unsupervised Learning: This approach seeks to uncover patterns, structures, or relationships within data without predefined labels or guidance.
3. Reinforcement Learning: In this paradigm, an agent learns decision-making by interacting with its environment, receiving feedback in the form of rewards or penalties. Through this iterative process, the agent refines its strategies based on experience and exploration.
4. Semi-Supervised Learning: Combining labeled and unlabeled data, this method is particularly beneficial when labeled data is resource-intensive or costly to acquire.
5. Transfer Learning: This technique leverages knowledge from pre-trained models on one task to improve performance on a related task. For instance, pre-trained models adapted to detect diseases in crops like wheat, rice, and maize have shown promise, especially in scenarios with limited labeled data.
6. Ensemble Learning: This approach enhances accuracy and robustness by combining multiple models. Techniques such as AdaBoost, Gradient Boosting, and Bagging are commonly employed in disease detection to improve prediction reliability and performance.

Machine learning techniques have demonstrated significant potential in solving complex problems, including crop disease detection, by leveraging their strengths in pattern recognition and decision-making.

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Globally, machine learning (ML) has achieved remarkable success in agriculture. Techniques such as Convolutional Neural Networks (CNNs) are widely used for image-based disease detection, while algorithms like Random Forests and Support Vector Machines (SVMs) excel in predictive analytics. However, the adoption of these technologies in Africa remains limited, primarily due to infrastructural and resource challenges. Although ML applications in agriculture have gained significant momentum in developed countries, there is a lack of studies addressing the specific challenges faced by African agriculture, particularly in Nigeria.

3.1. Review of related works

In a study by Jonathan et al., researchers explored real-time crop disease monitoring systems designed to provide smallholder farmers with immediate feedback. The research was conducted in a rural community of 100 smallholder farmers, focusing on diagnosing cassava diseases and delivering advisory recommendations. The study introduced a field-based recommendation system capable of real-time feedback on crop disease diagnosis.

This system was built using machine learning and natural language processing (NLP) techniques and relied on question-and-answer pairs collected from 100 farmers in Uganda. Various state-of-the-art algorithms were tested, with the Sentence BERT model (RetBERT) achieving the best performance, reflected in a BLEU score of 50.8%. The application integrates both online and offline functionalities to accommodate farmers in remote areas with limited internet access. The success of this study paves the way for larger trials to validate the system's potential in addressing food security challenges across sub-Saharan Africa.

A variety of machine learning (ML) techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), Random Forest (RF), and advanced deep learning architectures such as ResNet and Inception, were analyzed in terms of their methodologies, datasets, performance metrics, and real-world applications [18]. The review offered a critical evaluation of existing models, identifying their limitations and gaps. It highlighted that while ML-based approaches hold significant promise for improving agricultural disease management, there remains an urgent need for robust, scalable, and adaptable solutions capable of addressing diverse agricultural conditions and the complexities of crop diseases.

A detailed summary of CNN architecture and its applicability in image-based classification tasks was also presented [19]. The authors examined CNN applications for identifying diseases in vegetable crops, focusing on key research, datasets, and performance metrics. Their findings emphasized the transformative potential of CNN algorithms in revolutionizing crop disease diagnosis and management strategies. However, they also noted current limitations in applying computer algorithms to vegetable disease detection. Figure 3 illustrates the percentage distribution of CNN models utilized in detecting vegetable diseases.

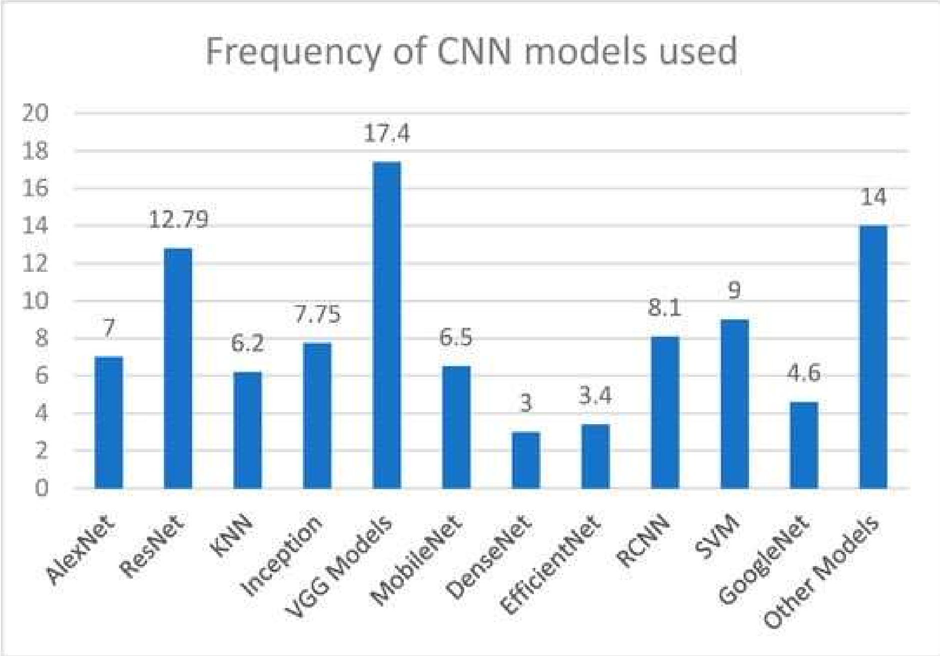

Figure 3: summary of CNN bases recommender systems. [19]

The VGG model emerged as the most commonly used, while DenseNet was the least utilized. Other models shown in the chart represent combinations of various architectures that individually had minimal contributions in the reviewed articles.

The effectiveness of a specific CNN in detecting vegetable diseases depends on several factors, including the availability and quality of annotations, the attributes of the provided images, environmental conditions during image acquisition, and the variability of disease symptoms across different instances. Despite the range of methodologies proposed for leaf disease identification, significant challenges remain, as outlined below.

3.2 . Limitations

- Adequate sample sizes are essential for ensuring deep learning (DL) networks can generalize features effectively.
- Despite advancements, only a limited number of diseases have been addressed, highlighting the need for expanded research to cover a broader spectrum of diseases.
- Current machine learning models depend heavily on manual feature extraction for performance evaluation, underscoring the need for automated feature extraction to enhance classification accuracy. Full automation requires models capable of detecting features independently with higher precision.
- Discriminating critical features in plant leaves using conventional image processing techniques remains challenging due to significant variability in disease symptoms. Automated analysis of these patterns requires diverse and comprehensive datasets.
- Some datasets are outdated and fail to account for newly mutated viruses or diseases. Additionally, diseases with similar symptoms but distinct treatments, or highly contagious diseases misinterpreted as mild, exacerbate the challenge of accurate diagnosis.
- Disease-level prediction remains a significant limitation, hindering the broader adoption of AI in agriculture.

- Real-time monitoring is not universally available on all farms, preventing continuous observation of progress or decline in crops.
- Many datasets are being reused by multiple researchers, leading to inefficiencies as time is spent re-analyzing data already studied by other groups globally.
- Variations in the contours of images can confuse AI models, hindering accurate identification of disease symptoms.
- Certain algorithms are computationally demanding, requiring significant storage and processing time. Optimizing these algorithms is necessary to deliver faster and more robust responses.

An enhanced recommendation system for Nigerian farmers has been developed [20]. Data from various sources, including the Nigeria Meteorological Agency, the Agronomy Department at the University of Ibadan, Ahmadu Bello University Zaria, and Federal University Wukari, were preprocessed using numpy and pandas. Four machine learning algorithms—Random Forest, Naïve Bayes, K-Nearest Neighbor, and Support Vector Machine (SVM)—were utilized, with Random Forest showing superior performance in accuracy, precision, recall, and F1 score. Naïve Bayes ranked second, followed by K-Nearest Neighbor, while SVM performed the poorest. The models successfully recommended crops suited to specific climates and soils, though SVM was the least effective. This study highlights the importance of accurate crop recommendations for optimizing agricultural productivity.

Mahenge et al. examined the knowledge and technological gaps related to the application of AI-based technologies for early plant disease detection and pest prediction, recommending appropriate curative measures [21]. They utilized the PRISMA framework for conducting systematic reviews on the state-of-the-art AI and deep learning techniques for crop disease identification and pest prediction in developing countries. The findings revealed that traditional methods for plant disease management face several challenges, including high labor costs, low detection and prediction accuracy, and negative environmental impacts. Moreover, the growing demands of data-intensive and computationally demanding tasks required for plant disease classification using traditional machine learning methods pose difficulties, such as prolonged processing times and limited storage capacity.

To recommend the most suitable seed for specific soil conditions with high accuracy and efficiency, a recommendation system using an ensemble model with a majority voting technique, incorporating Random Tree, K-Nearest Neighbor, and Naïve Bayes as learners, was proposed [22]. This approach aimed to maximize production and profit for farmers.

Advanced image identification techniques were applied to a dataset consisting of highly detailed aerial photographs of vineyards [23]. After each algorithm and process was carefully optimized, a comprehensive comparison of the results was conducted, focusing on baseline and DTE, highlighting the differences in accuracy and performance.

A framework utilizing machine learning and data mining to bridge knowledge gaps and address key issues in animal sciences was presented in [24]. With data-intensive technologies, animals can be continuously monitored throughout production, and the collected data can be used to enhance their health, welfare, performance, and environmental impact.

3.3 Potentials of machine learning in Agricultural practices

The application of machine learning (ML) data-driven techniques has the potential to yield significant advancements in agricultural practices, which could ultimately result in the following outcomes [25]:

i. Enhanced Crop and Livestock Yields: This can be achieved through precise disease diagnosis and management, location-specific soil analysis, and improved seed variety assessments.

ii. Improved Value Chain Linkages: The integration of various stakeholders, including input suppliers, farmers, financial institutions, extension agents, and markets, can be facilitated through the ease of data sharing and communication.

iii. Reduction in Production Costs: The adoption of more efficient and cost-effective techniques at each stage of production, such as land preparation, planting, weeding, fertilization, and harvesting, can significantly reduce overall production costs.

iv. Pathway to Agricultural Sustainability and Self-Sufficiency: Increased profitability and production will lead to higher participation in farming, fostering self-sufficiency in agricultural products that can meet the growing demands of the population.

v. Increased Contribution of Agriculture to National GDP: The rise in production, employment, and the establishment of new micro, small, and medium-sized enterprises (MSMEs) in agrotech and agro-processing will bolster the agricultural sector's contribution to the national economy.

vi. Global Leadership in ML Technology Advancement: The integration of ML technologies into Nigerian agriculture could position the country as a leader in ML innovation, fostering local research and the creation of ML incubation labs that could propel Nigeria to the forefront of global advancements in ML.

4. Challenges Hindering the Application of Machine Learning in Nigerian Agricultural Practices

Despite the significant benefits associated with the use of machine learning in Nigerian agriculture, several challenges hinder its effective implementation. These challenges can be broadly categorized into personnel, infrastructural, and technical issues, including:

i. Lack of Sufficient and High-Quality Datasets: The success of machine learning applications relies heavily on the availability of quality data. In Nigeria, the nascent stage of ML and deep learning (DL) development presents a significant challenge due to the scarcity of reliable datasets for training algorithms. As a result, developers may have to generate their own datasets, which can lead to issues such as overfitting, thereby compromising the accuracy and reliability of the models.

ii. Inadequate Infrastructure: The telecommunication and electricity infrastructure in Nigeria is underdeveloped, particularly in rural areas where the majority of agricultural activities take place. These infrastructures are essential for the effective implementation of modern ICTs, which are crucial for achieving optimal performance and meeting desired objectives. While satellite and wireless technologies have been introduced in Nigeria, they are predominantly concentrated in urban centers, and even here, the infrastructure often remains insufficient. Issues such as low bandwidth and the need for an enhanced internet backbone further hinder progress.

iii. High Illiteracy Rates in Rural Areas: Literacy is a critical barrier to participation in knowledge-driven societies. A significant proportion of the rural population in Nigeria, particularly women, remains illiterate. Much of the pictorial and audiovisual information associated with machine learning technologies is accompanied by text, which places these individuals at a disadvantage. They lack the necessary skills to fully leverage the benefits of ML technologies. Consequently, the involvement of intermediaries, such as extension agents, may be essential to assist these farmers in accessing and utilizing these technologies effectively.

iv. Privacy and Security Concerns: The absence of clear policies and regulations regarding the use of artificial intelligence, not only in agriculture but across various sectors, raises numerous legal challenges. Precision agriculture and smart farming, while offering significant benefits, introduce concerns related to privacy and security. Threats such as cyberattacks and data breaches pose serious risks to farmers, particularly as many farms remain vulnerable to such threats due to inadequate protective measures.

4.1 Factors affecting the adoption of digital technologies in farm practices in Nigeria:

Nigeria's agricultural sector is undergoing significant transformation. Mughele et al. identified several factors driving the adoption of digital tools, such as machine learning, in the country [26]:

a) Rapid Technological Advancements: The growing affordability and accessibility of IoT sensors, big data tools, and machine learning algorithms have made precision farming more attainable for Nigerian farmers.

b) Climate Change Challenges: Like many other nations, Nigeria faces the detrimental impacts of climate change. Machine learning plays a crucial role in developing adaptive strategies that optimize resource utilization, minimize waste, and mitigate climate-related risks.

c) Food Security Imperative: With a rapidly expanding population, Nigeria must increase its food production to meet rising demand. This highlights the critical need for adopting machine learning in agriculture to enhance productivity and ensure food security.

d) Government Commitment: The Nigerian government has demonstrated its commitment to agricultural modernization through initiatives such as the Green Alternative Policy and the National Digital Agriculture Infrastructure.

While precision farming is still in its early stages in Nigeria, the integration of machine learning in agriculture presents promising opportunities, including:

e) IoT-Enabled Farming: IoT sensors offer the capability to monitor soil conditions, weather patterns, as well as crop and animal health in real-time, providing valuable data to support informed decision-making.

f) Data-Driven Insights: Machine learning and data analytics can transform raw data into actionable insights, facilitating the optimization of crop management, resource allocation, and pest control.

g) Enhanced Crop Yields: Precision agriculture techniques have the potential to substantially boost agricultural productivity, thereby ensuring food and animal security while contributing to economic growth.

h) Youth Engagement: The incorporation of technology into agriculture offers the opportunity to attract younger generations to the sector, revitalizing it and fostering the emergence of digital farming entrepreneurs.

5. Conclusions

The literature review reveals that most machine learning models have the potential to address the limitations inherent in traditional methods of manual feature extraction and classification. However, the primary challenge lies in the data sources and testing environments. Much of the existing research relies on public datasets, yet studies should ideally be conducted using data collected directly from agricultural fields. Weather and geological conditions significantly influence disease characteristics, meaning that data from one geographical region may not be applicable to another. For instance, training a model with data from the US and applying it to disease detection in Nigeria may result in significant discrepancies in accuracy.

The wide variety of vegetable diseases, coupled with the variability in symptoms across cases, underscores the need for more resilient and adaptable models. This necessitates advancements in feature extraction techniques, reorganization of model architectures, and the integration of advanced approaches such as ensemble learning and transfer learning.

This review highlights the differences in the accuracy of various models for disease detection in vegetables, which are highly susceptible to a wide range of diseases, leading to significant economic losses. The implementation of Convolutional Neural Networks (CNNs) has shown promise in reducing these losses by enabling early-stage disease detection.

Furthermore, this review stresses the importance of global data sharing among research communities. To fully harness the potential of CNNs and deep learning (DL) in transforming plant disease detection and advancing agricultural sustainability, interdisciplinary collaboration between computer scientists, plant pathologists, and agronomists is crucial. Additionally, ongoing research and innovation in model development are necessary. Future work should further investigate the issues identified in this study. In particular, the potential role of the Internet of Things (IoT) in plant disease detection remains largely unexplored, but it holds great promise for timely and accurate detection, which could lead to more effective interventions.

Recommendations

The detection of disease stages is critical. The model should be capable of identifying the stage of the disease (e.g., curable, non-curable, or rotten) to enable farmers to take timely and appropriate action, minimizing unnecessary delays.

Improvements in feature extraction techniques are essential to enhance the accuracy and efficiency of data identification and monitoring. This will help ensure more reliable disease detection and management.

Real-time farm monitoring should be implemented to provide continuous surveillance of crops. This will enable farmers to determine the optimal timing for interventions, such as the application of pesticides, and to assess the recovery time or potential loss of the harvest.

Diseases with similar symptoms often present challenges in identification. Highly contagious diseases, for example, can be managed with early intervention. The model should exhibit high precision in distinguishing between diseases with similar symptoms to avoid misdiagnosis.

It is essential for farmers to have clear knowledge of the time remaining to save their crops or the time required to cure the infected crops. Accurate identification of the disease stage will greatly assist in determining the urgency of the intervention.

The application of pesticides and other chemicals depends on the severity of the disease. The model should recommend the appropriate concentration of pesticides needed for effective crop protection, preventing unnecessary expenditure and minimizing losses in production.

The integration of IoT technologies with the output algorithms used in farm management systems can significantly enhance data sharing and usage across different regions globally. This integration will enable real-time monitoring and decision-making, adapting to changes in environmental conditions and ensuring timely and efficient interventions.

Multidimensional concatenation of data could contribute valuable insights, particularly regarding plant-insect interactions. This approach can offer a more comprehensive understanding of the agricultural ecosystem and improve disease management strategies.

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