School of Informatics

Informatics Research Review
A Study of Disease Detection Deep Learning Techniques on Cash Crop for Developing Countries

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Abstract

The abstract is a short concise outline of your project area, **of no more than 100 words**.

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1 Introduction

With agriculture contributing 4% of the global gross domestic product (GDP) and up to 25% of GDP in some of the developing nations, its significance to economic growth is undeniable.[1] However, the cash crop productivity face significant obstacles such as pests, crop diseases, and environmental problems. These problems cause yield losses and have an impact on staple foods and farmers' sources of income. Moreover, in developing countries, cash crop disease detection is especially important since it directly affects the country's food security, economic stability, and citizens' quality of life. In this paper, we have categorised the cash crops into four: cereals (wheat and rice), commercial crops (cotton and sugarcane), horticultural crops (citrus and mango), and oilseeds (sesame and sunflowers).[2] Furthermore, plant-parasitic nematodes and insect pests worsen agricultural issues in the area. Using deep learning and other technologies, early and accurate crop disease detection is necessary to meet these challenges.

In order to solve these problems, deep learning technology must be applied. Deep learning has the potential to transform crop disease detection by offering rapid, non-invasive, and accurate assessments of crop health. With the use of this technology, agricultural researchers and stakeholders can keep an eye on crop conditions in real time, spot disease outbreaks or pest infestations early on, and treat crops promptly to reduce losses. The application of deep learning in developing countries cash crop agriculture has the potential to boost productivity, encourage ecologically friendly farming practices, and improve the sector's overall resilience.

The objective of this review paper is to methodically evaluate the state of deep learning applications for cash crop disease detection in developing countries. The countries under examination are Ethiopia, Sudan, China, Bangladesh, India, and Pakistan, which are listed by the UN under the heading "Developing economies by region".[3] The study will also examine current approaches and offer recommendations for additional research, along with useful implications for academics, policymakers, and farmers who want to enhance crop disease prevention and agricultural sustainability in these nations. With the region's distinct agricultural landscape and budgetary constraints in mind, the emphasis will be on the application of deep learning technologies in developing nations, exploring their efficacy, challenges, and opportunities for widespread adoption. In order to achieve that, we have sectioned our review as follows:

- In section 2, we provide a brief background on crop descriptions, some disease that pose a significant threat to the crops, the traditional methods used to detect the diseases, and how different deep learning techniques can be used for disease detection.
- In section 3, we present the main body of the literature review.
- In section 4, we list the limitations, challenges and considerations that face crop disease detection projects.
- Section 5 provides our summary and conclusions, and the review's last section acts as a guide for further investigation.

This review deliberately did not include research that does not use deep learning techniques and is focused on detecting cash crop diseases in developing countries only. There is also a disregard for studies with little emphasis on actual application of solutions in the real world or those not relevant to developing countries. We have also excluded any paper that uses "PlantVillage" dataset solely as it is crowd-sourced from multiple countries.

2 Background

2.1 Crop Description

Developing countries have diverse agricultural landscapes with varying climatic conditions. Cultivating a wide variety of cereals is essential to meeting the dietary needs of the populations living there. Prized for its ability to withstand dry conditions, sorghum is a staple grain and vital feed for livestock. In the meantime, millet, which is resistant to drought, becomes an essential food source, especially in areas where there is a shortage of water. The origins of wheat, a staple food consumed by people worldwide, can be found in regions of South Asia and parts of Africa that enjoy mild temperatures. Over half of the world's population is fed by rice, which grows abundantly in tropical regions, and maize's versatility helps meet urgent food security needs in Latin America and Africa.

Developing countries greatly benefit economically from oilseed crops; sesame seeds are particularly notable for their high oil content, which is useful for both nutrition and cooking. Because they provide essential oils and proteins, groundnuts, also known as peanuts, are essential to smallholder farmers. Due to the growing demand for its health-promoting oil, sunflower cultivation is becoming more and more popular, making it a significant player in both the domestic and international edible oil markets.

Many developing economies are based mostly on commercial crops, with cotton emerging as a key cash crop that supports the textile sector and gives farmers a vital source of income. The main crop used to produce sugar is sugarcane, a tropical staple that is important for exports as well as domestic consumption.

Developing countries face a delicate balance between local sustenance and economic development in the field of horticulture, where fruits and vegetables flourish. In addition to being grown for local consumption, okra, onions, and tomatoes are also grown for export, which promotes dietary diversity and economic expansion. Well-liked horticultural products like mangoes and citrus fruits are profitable exports that boost foreign exchange profits and give farmers work opportunities in addition to being a valuable addition to the local diet.

2.2 Cash Crop Diseases in Developing Countries

2.2.1 Common crops and diseases:

Cash crop diseases pose a significant threat to the agricultural landscapes of developing countries, as multiple important crops are vulnerable to different types of pathogens. When it comes to cereals, fungi, bacteria, and viruses pose a threat to maize, a staple that is crucial for tackling issues related to food security. Similar to this, rice faces a unique set of pathogenic difficulties despite being the main food crop that feeds more than half of the world's population. Mangoes and citrus fruits, which are valuable crops for export and local consumption, are examples of horticultural crops that are susceptible to diseases that can negatively affect yields and quality.

2.2.2 Impact of diseases:

Crop disease prevalence in developing nations has significant economic and social ramifications. Whole communities are affected when cash crops, such as rice and maize, perish from diseases. Reduced yields have two negative economic effects: they lower farmers' incomes, which exacerbates poverty; and they restrict the supply of these staple foods, which increases food insecurity. Diseases that affect horticulture crops also affect the export market, which lowers foreign exchange earnings. Crop diseases have an impact on the economy, but they also exacerbate social problems like malnutrition because lower crop yields have an impact on the cost and accessibility of wholesome food. All things considered, the interaction between diseases that affect cash crops and the fallout from them exacerbates already-existing issues, feeding the vicious cycle of hunger, poverty, and food insecurity in these vulnerable areas. It takes a multifaceted strategy to address these problems, combining societal and agricultural interventions to create resilience and long-term fixes.

2.3 Traditional Disease Detection Methods

Crop disease identification and management have benefited greatly from the use of traditional agricultural disease detection techniques, which are especially common in developing nations. These techniques include visual inspection, symptom-based diagnosis based on conventional wisdom, and depending on farmers' trained eyes to identify symptoms. Traditional methods are supplemented by field surveys and sampling, community knowledge exchange, and weather and environmental monitoring. Although these techniques have shown to be successful, they have drawbacks like subjectivity and reliance on local expertise. By combining these age-old techniques with contemporary technology, disease detection accuracy and efficacy can be improved. Building resilient and sustainable agricultural systems requires developing countries to strike a balance between traditional methods and cutting-edge technologies as they negotiate the complexities of agriculture.

2.4 Deep Learning for Disease Detection

A branch of machine learning called deep learning has become a potent instrument for agricultural disease detection. Neural networks, especially Convolutional Neural Networks (CNNs), which are intended to imitate the structure of the human brain, are at the centre of it all. Convolutional layers are used by CNNs to automatically learn and extract hierarchical features from visual data, which makes them excellent image analysts. Because of their ability to recognise complex patterns, they are especially useful for tasks like identifying crop diseases.

Utilising CNNs for automatic disease detection in different crops has advanced significantly in recent years, addressing issues that developing nations face. Research has explored the use of deep learning to identify diseases in horticultural crops like citrus fruits and mangoes, as well as cash crops like rice and maize. These methods train CNN models on large annotated image datasets, which helps the models identify subtle visual cues that may indicate certain diseases. CNNs' ability to adjust to various crop types and diseases demonstrates the deep learning's adaptability in agricultural settings.

There are many benefits to using deep learning for disease detection, but developing countries stand to gain the most from it. Accuracy is a noteworthy benefit; CNNs can identify diseases with high precision, which lowers the risk of incorrect diagnoses. The rapid and scalable analysis of large datasets made possible by the efficiency of deep learning models facilitates the timely detection of diseases. Furthermore, the process is streamlined and requires less specialised knowledge thanks to the possibility of automation in the on-field deployment of these models or through remote sensing technologies. This is particularly important in areas where agronomic knowledge may not be widely available. In these susceptible areas, the decreased dependence on manual inspection and the possibility of early detection lead to more efficient disease control, reducing crop losses and promoting sustainable farming methods. Deep learning's integration into agricultural systems has the potential to revolutionise disease detection as it develops further, providing creative ways to improve food security and economic stability in developing nations.

To improve farming decision-making, multimodal deep learning in agriculture combines data from multiple sources, including sensor and satellite imagery. This method makes use of sophisticated models to enable a thorough examination of crop health, environmental influences, and yield projections. The incorporation of deep learning methodologies facilitates the discernment of significant patterns from intricate datasets, providing invaluable perspectives for precision agriculture, pest management, and sustainable resource administration. This novel strategy has great potential to transform agriculture by increasing food production's sustainability and efficiency.

3 Literature Review

3.1 Cereals (millet, wheat, rice and maize)

Wheat:[4]

Wheat Rust Disease Detection Using Deep Learning[5]: The study examines prevalent wheat rusts in **Ethiopia** and talks about earlier uses of CNNs in the identification of plant diseases. The study presents a new CNN architecture and describes how it was implemented and trained on a dataset of 2,113 images that had been enhanced using different methods. The model's remarkable accuracy is demonstrated by the experimental results, which show that it performs best on RGB color-segmented images, reaching 99.76%.

Automated Wheat Plant Disease Detection using Deep Learning: A Multi-Class Classification Approach[6]: The literature review paper comprehensively explores the landscape of wheat disease detection using machine learning and computer vision techniques. The study, written by Sheenam, Sonam Khattar, and Tushar Verma, discusses how crucial it is . The writers give a thorough summary of current techniques, going over strategies like feature extraction, segmentation, and classification. A novel automated system for detecting wheat disease is presented in this paper. It is built on a refined *VGG19* deep convolutional neural network. On the validation dataset, the suggested model achieves a high accuracy of 97.65%, outperforming current algorithms. The data was collected from multiple wheat farms in **Pakistan**'s **Peshawar** and **Dir**, and 1,266 images of patients with both pathological (Stip Rust, Septoria) and healthy conditions were used.

Wheat Disease Detection And Growth Stage Monitoring Using Deep Learning Architectures[7]: A novel model to enhance the diagnosis of diseases in wheat plants was suggested to effectively capture both local and global information by fusing the strong feature extraction capabilities of a CNN with the multi-head attention feature of a vision transformer. This allows for a thorough description of image features. Additionally, to get around the drawbacks of growth monitoring techniques and precisely track the stages of wheat plant growth, an ensemble approach utilising *DenseNet201*, *InceptionV3*, and *InceptionResNetV2* models is used. The enhanced vision CNN model performs remarkably well in the experimental results, achieving an astounding 99.4% accuracy in disease detection. Additionally, the ensemble models show 88.5% accuracy in identifying the growth phase. **Bangladeshi** crop datasets from Kaggle are used to detect diseases. The dataset is divided into three different classes: Wheat Brown Rust (1128 images), Wheat Yellow Rust (1156), and Healthy Crops (1497 images).

Rice

Rice Leaf blight Disease detection using multi- classification deep learning model[8]: In this paper, a convolutional neural network (CNN) architecture-based deep learning method for detecting rice leaf blight (RLB) disease in rice crops is presented. A dataset of 3000 real-time photos taken from Punjab, India's rice fields is used in the study. There are two stages to the experiment: multi-classification based on the severity of RLB infection and binary classification that separates healthy from RLB-infected crops. In binary and multi-classification, the suggested CNN model achieves excellent accuracy of 94.33% and 95.3%, respectively. The study highlights how important it is to treat crop diseases like RLB in order to improve crop quality, technological advancement, research and development, and industry innovation. Larger datasets and consideration of additional severity levels in RLB disease detection are among the challenges faced during the study.

Generative Adversarial Network-based Augmented Rice Leaf Disease Detection using Deep Learning[9]: The study uses Super Resolution-GAN (SRGAN) as a data augmentation technique to address the problem of limited data availability for rice leaf disease detection. Focusing on an Indian dataset with 5932 images representing four different diseases, the authors experiment with SRGAN to improve the balance between healthy and diseased images. The study then uses classification models to determine rice leaf diseases, such as DenseNet121, DenseNet169, MobileNetV2, and VGG16. The results demonstrate the efficacy of SRGAN-augmented datasets, particularly with DenseNet169 and MobileNetV2 achieving a high accuracy of 94.30%, showcasing the potential of this approach in improving disease detection accuracy despite the initial data limitations.

Year	**Country**	**Crop Category**	**Crop**	**No of Images**	**Dataset Classes**	**Training Model**	**Optimization Algorithm**	**Compared Multiple Models**	**Performance**
2021 [5]	Ethiopia	Cereals	Wheat	2,113		CNN	-	-	99.76%
2023 [6]	Pakistan (Peshawar, Dir)	Cereals	Wheat	1,266		VGG19	-	-	97.65%
2023 [7]	Bangladesh	Cereals	Wheat	-		DenseNet201, InceptionV3, Inception-ResNetV2	-	Yes	99.4% (Disease Detection), 88.5% (Growth Phase)
2022 [8]	India (Punjab)	Cereals	Rice	3,000		CNN	-	-	94.33% (Binary), 95.3% (Multi-Class)
2022 [9]	India	Cereals	Rice	5,932		DenseNet121, DenseNet169, MobileNetV2, VGG16	-	Yes	94.30%

Table 1: Summary of Research Papers on Cereal Crops Disease Detection

3.2 Oilseeds (sesame and sunflowers)

Sesame:

Sesame Seed Disease Detection Using Image Classification (2021)[10]: Using a dataset of 1,695 images of **sesame leaves** from **Gadarif State**, **Sudan**, this study compares a developed CNN model to well-known models like *VGG16*, *VGG19*, *Resnet50*, *Resnet101*, and *Resnet152*. There are two disease classes and one healthy class in the dataset. With the help of the Adam optimizer, and a 90.77% training accuracy and 88.5% testing accuracy, the developed model outperformed the competition, demonstrating its potential for effective disease detection in sesame cultivation. This study showed how CNNs have a great deal of potential for early disease detection ese sesame, a vital crop.

Sesame Disease Detection Using a Deep Convolutional Neural Network (2022)[11] or Detection of Sesame Disease Using a Stepwise Deep Learning Approach[12]: Tadele et al. developed a methodical *deep convolutional neural network (DCNN)* to efficiently identify different forms of sesame diseases, particularly the visually ambiguous "neck eye" varieties, with the goal of enhancing farmer productivity in **Ethiopia**. The six image processing steps in their methodology are acquisition, preprocessing, segmentation, augmentation, feature extraction, and classification. Using 450x680 resolution smartphone photos, they trained the *DCNN* on a dataset of 540 labelled images covering Phyllody infections, Bacteria Blight infections, and healthy leaves. This model showed remarkable accuracy, with 99% training and 98% testing accuracy. It can be applied to higher sesame crop yields and more precise disease detection.

Sunflowers:

A Hybrid Model for the Classification of Sunflower Diseases Using Deep Learning[13]: The study uses a hybrid model of deep learning techniques to classify diseases. With a focus on Verticillium wilt, Phoma blight, Alternaria leaf blight, and Downy mildew in sunflowers, the hybrid model combines *VGG-16* and *MobileNet* using the stacking ensemble learning method. The suggested model outperforms other models (*VGG16*, *MobileNet*, *AlexNet*, *InceptionV3*, and *DenseNet121*) with an impressive accuracy rate of 89.2%. The authors use Google images to curate their dataset and have divided it into 5 classes of the sunflower which consist of 4 diseases (Alternaria leaf spot, Downy Mildew, Phoma Blight, and Verticillium wilt), and 1 is healthy leaf class.

Sunflower seeds classification based on sparse convolutional neural networks in multi-objective scene[14]: The paper proposes a novel approach—a multi-objective sunflower seed classification method based on sparse convolutional neural networks. The technique uses *YOLOv5* to detect objects in videos that are sunflower seeds, and then it uses a *ResNet-based model* for classification. The model is compressed to a 92% reduction in parameters by the study using the Lottery Ticket Hypothesis and Iterative Magnitude Pruning. The paper also describes the process of creating a dataset, which includes selecting a balanced sample for training, validation, and testing sets, classifying images into six categories, and detecting objects in ten chosen videos.

AI-Driven Sunflower Disease Multiclassification: Merging Convolutional Neural Networks and Support Vector Machines[15]: In order to predict diseases in sunflowers, the research paper presents a novel method that combines models from *Support Vector Machine (SVM)* and *Convolutional Neural Network (CNN)*. The proposed model, trained on a dataset gathered from the Bangladesh Agricultural Research Institute demonstration farm, consists of three convolutional layers, three max-pooling layers, and two fully connected layers, with the second fully connected layer incorporating SVM. With an accuracy of 83.59% and an overall F1 score of 83.45%, the results show a high degree of accuracy. The model successfully classifies a range of sunflower diseases, with accuracy values between 80.65% and 85.37%. Through meta-analysis of layer parameters, the study demonstrates how the accuracy of the model is significantly impacted by the second fully connected layer.

3.3 Commercial crops (cotton and sugarcane)

Sugarcane:

Year	Country	Crop Category	Crop	No of Images	Dataset Classes	Training Model	Optimization Algorithm	Compared Multiple Models	Performance
2021	Sudan	Sesame	Sesame Leaves	1,695	3 Classes	VGG16, ResNet, Developed Model	-	Yes	89.2% Accuracy
2022	Ethiopia	Sesame	Sesame Diseases	540	3 Classes	CNN, SVM	-	Yes	83.59% Accuracy, 83.45% F1 Score
2021	Sudan	Sunflower	Oilseeds Crops	1,695	5 Classes	VGG16, MobileNet, AlexNet, InceptionV3, DenseNet121	Adam	Yes	89.2% Accuracy
2022	-	Sunflower	Oilseeds Crops	-	6 Categories	YOLOv5, ResNet-based Model	Lottery Ticket Hypothesis, Iterative Magnitude Pruning	Yes	92% Parameter Reduction
2023	Bangladesh	Sunflower	Oilseeds Crops	-	-	CNN	SVM	-	83.59% Accuracy, 83.45% F1 Score

Table 2: Summary of Research Papers on Oilseeds Crops Disease Detection

Sugarcane Disease Recognition using Deep Learning[16]: In this paper, Militante et. al. have identified and categorised the diseases in sugarcane plants by examining through the use of deep learning techniques. The study, which emphasised the importance of early detection, it focuses on the financial impact of sugarcane diseases on farmers. With an astounding accuracy of 95%, the proposed deep learning model—a *Convolutional Neural Network (CNN)*—is trained on a dataset of 13,842 images of sugarcane with both disease-infected and healthy leaves. The study took place in the **Philippines**.

Detecting Sugarcane Diseases through Adaptive Deep Learning Models of Convolutional Neural Network[17]: Militante et. al. have also tackled this problem by writing another research paper using Convolutional Neural Networks (CNNs), which are adaptive deep learning models. To achieve the highest accuracy rate in identifying sugarcane diseases, the research integrates multiple CNN architectures, such as *StridedNet*, *LeNet*, and *VGGNet*. The models are trained on a dataset of 14,725 photos of disease-ridden and healthy sugarcane leaves. During training, the models reach a maximum accuracy rate of 95.40%. With an accuracy rate of 95.40%, *VGGNet* is the most successful model; *LeNet* comes in second with 93.65%, and *StridedNet* comes in third with 90.10%.

A Novel Deep Learning Framework Approach for Sugarcane Disease Detection[18]: In the context of sugarcane agriculture, this literature review investigates a novel deep learning framework for identifying diseased sugarcane plants, where disease detection is critical to crop health maintenance. The dataset was formed by collecting images of diseased and non-diseased sugarcane from Mawana Sugar Mill Pvt. Ltd, **India**. Three distinct feature extractor *scenarios—Inception v3*, *VGG-16*, and *VGG-19*—are used in the study, and different classifiers are trained on these pre-trained models. Deep learning algorithms like neural networks and hybrid *AdaBoost* are thoroughly compared with traditional machine learning algorithms like *SVM*, *SGD*, *ANN*, *naive Bayes*, *KNN*, and *logistic regression*. Orange software is used to calculate statistical measures like accuracy, precision, specificity, AUC, and sensitivity. The scenario with VGG-16 as the feature extractor and SVM as the classifier has the highest accuracy, at 90.2%.

Sugarcane leaf disease detection through deep learning[19]: In response to this issue, N.K. Hemalatha et. al.s literature review introduces a novel approach employing a deep learning neural network architecture for the automatic identification of sugarcane diseases. A dataset comprising 2940 photos of sugarcane leaves from six distinct classes—five diseased and one healthy—was utilised by the researchers. The photos were taken at different cultivation fields, such as the University of Agricultural Sciences and neighbouring farms in Bangalore and Mandya, **India**. *Xception*, *Inception-v4*, *Inception-ResNets*, *LeNet*-5, *AlexNet*, *VGG-16*, *Inception-v1*, *Inception-v3*, *ResNet-50*, and *ResNeXt-50* are a few of the well-known CNN architectures that are employed for the classification task. The research demonstrates that LeNet-5 performs better at classifying images than other network models. The proposed model utilizes convolutional neural networks trained on a dataset comprising around 3000 images of affected leaves, achieving an impressive accuracy rate of 96%.

Sugarcane Diseases Identification and Detection via Machine Learning[20]: In an attempt to address the issue of sugarcane diseases pose a significant threat to the global sugarcane market, impacting crop yield and quality and thus resulting in financial losses for farmers and reduced supplies for the sugar industry, Mostafizur Rahman Komol et al.'s review of the literature presents a research project that uses the *YOLO algorithm* to detect three types of sugarcane diseases. *YOLO version 8* showed remarkable accuracy of 96.67% when trained and evaluated on an image dataset associated with sugarcane disease, highlighting its potential for early diagnosis and treatment.

Cotton:

Cotton leaf disease identification using pattern recognition techniques[21]: The study addresses the critical need for early and accurate identification of leaf diseases on cotton plants to mitigate potential yield losses. The proposed pattern recognition system focuses on identifying and classifying three specific cotton leaf diseases—Bacterial Blight, Myrothecium, and Alternaria. Images utilized for the study are sourced from fields at the Central Institute of Cotton Research in Nagpur, **India**, along with cotton fields in Buldana and Wardha districts. Image segmentation employs an active contour model, and features for training an adaptive neuro-fuzzy inference system are extracted using Hu's moments. The classification accuracy of the system is reported at 85 percent, underscoring its potential for effective disease diagnosis in cotton crops.

Detection of Cotton Plant Diseases Using Deep Transfer Learning [22]: This paper addresses the ongoing challenges in agriculture in **India**, especially with regard to cotton diseases, by utilising deep learning techniques and taking advantage of its ability to process and classify images quickly, cheaply, and accurately. Beyond other state-of-the-art methods, the network architecture combines the strengths of the *Xception* component and the *ResNet* pre-trained on *ImageNet*. To ensure accurate disease detection, every convolution layer in the dense block concentrates on picking up minute details. The deep convolutional neural network method for plant leaf disease detection is characterised by the use of pre-trained models from large datasets that have been optimised for particular tasks using domain-specific information. The effectiveness of *ResNet-50* is demonstrated by the experimental results, which show training accuracy of 95% and validation accuracy of 98% along with training loss of 33% and validation loss of 50%.

Detection of Cotton Plant Disease for Fast Monitoring Using Enhanced Deep Learning Technique[23]: In order to detect diseases in plants, this study analyses transfer learning methods and suggests a sequential deep convolutional neural network that can distinguish between healthy and unhealthy plants. The suggested model outperforms pre-trained models such as VGG16, ResNet50, and ResNet152V2 in terms of accuracy and speed. This dataset, which includes images of both healthy and diseased cotton plants and leaves, was gathered from the internet and the Cotton Disease database. It is especially pertinent to **Western Indian** regions like Gujarat, Maharashtra, and Karnataka, which are major cotton-growing areas. The suggested model's effectiveness on unknown data is demonstrated by the experimental results, which show a noteworthy test accuracy of 98.11%, surpassing transfer learning approaches like 96.04% for *VGG16*, 71.70% for *ResNet50*, and 98.01% for *ResNet152V2*.

Deep Learning Technique Detection for Cotton and Leaf Classification Using the YOLO Algorithm[24]: Cotton, a globally significant crop, faces susceptibility to various plant diseases, leading to substantial yield reduction. Timely detection of diseases is crucial for prompt diagnosis and effective treatment. To address this, a deep learning approach utilizing the *YOLOv3* algorithm was implemented, presenting a robust cotton plant classification system. *YOLOv3*, renowned for real-time object identification, demonstrated exceptional performance in detecting and classifying both healthy and damaged plants and leaves. The applied model achieved a notable mean Average Precision (mAP) score of 96.09%, accompanied by a high training accuracy of 96.79% and validation accuracy of 92.26%. Testing results showcased impressive detection accuracy in video frames, ranging from 98% to 99%, while live stream image frames exhibited a range of 74% to 99%.

Image Classification Using Deep Learning Algorithms for Cotton Crop Disease Detection[25]: The traditional method of disease detection, reliant on visual inspection and past knowledge, is acknowledged for its limitations, particularly the risk of incorrect diagnoses leading to the excessive use of pesticides and potential harm to plants. In response to these challenges, Bavaskar et. al. introduces a novel system employing deep learning-based image classification of crop leaves for the early detection of three cotton diseases: Bacterial Blight, Curl Virus, and Fusarium Wilt. The study evaluates the performance of four distinct deep learning architectures and highlights the *ResNet152 V2* architecture as the most effective, achieving a remarkable accuracy of 99.12% on the training dataset and 98.26% on the testing dataset.

3.4 Horticultural crops (okra, onions, tomatoes, citrus, mango, etc.)

Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model[26]: The major drop in citrus fruit yield due to diseases is the main topic of this study. The authors suggest a deep learning-based automated detection system, namely a *convolutional neural network (CNN)* model, to address this problem. The CNN model is intended to discern between citrus fruits and leaves that are in good health and those that are afflicted with common diseases such as greening, canker, scab, black spot, and Melanose. The suggested model extracts discriminative features by integrating multiple layers, outperforming other cutting-edge deep learning models on the Citrus and PlantVillage datasets. The CNN Model shows to be a useful decision support tool for farmers in the classification of citrus fruit and leaf diseases, with a test accuracy of 94.55%.

Year	Country	Crop Category	Crop	No of Images	Dataset Classes	Training Model	Optimization Algorithm	Compared Multiple Models	Performance
2019 [16]	Philippines	Commercial crops	Sugarcane	13,842	-	CNN	-	-	95%
2019 [17]	Philippines	Commercial crops	Sugarcane	14,725	-	StridedNet, LeNet, VGGNet	-	Yes	95.40%
2020 [18]	India	Commercial crops	Sugarcane	-	-	Inception v3, VGG-16, VGG-19	SVM	Yes	90.2%
2021 [19]	India	Commercial crops	Sugarcane	2,940	6 Classes (5 diseased, 1 healthy)	Xception, Inception-v4, LeNet-5, VGG-16, Inception-v1, Inception-v3, ResNet-50, ResNeXt-50	-	Yes	96%
2023 [20]	-	Commercial crops	Sugarcane	-	3	YOLO version 8	-	-	96.67%
2015 [21]	India	Commercial crops	Cotton	-	3	Active Contour Model, Adaptive Neuro-Fuzzy Inference System	-	-	85%
2021 [22]	India	Commercial crops	Cotton	-	-	Xception, ResNet-50	Pre-trained on ImageNet	Yes	95%, 98%
2021 [23]	Western India	Commercial crops	Cotton	-	-	VGG16, ResNet50, ResNet152V2	-	Yes	VGG16 (96.04%), ResNet50 (71.70%), ResNet152V2 (98.01%)
2022 [24]	-	Commercial crops	Cotton	-	-	-	-	-	96.09% (mAP), 96.79% (Training), 92.26% (Validation)
2022 [25]	-	Commercial crops	Cotton	-	3	Four architectures (ResNet152 V2)	-	Yes	99.12% (Training), 98.26% (Testing)

Table 3: Summary of Research Papers on Commercial Crops Disease Detection

4 Challenges and Considerations

4.1 Data Acquisition and Availability

Obtaining high-quality image data in settings with limited resources is a major obstacle to deep learning model implementation in agriculture. Robust disease detection models may not be developed if advanced imaging technology and the necessary expertise are not readily available. Leveraging the ubiquitous use of smartphones presents one possible avenue for solution. Equipped with cameras, these devices can serve as practical tools for capturing images of crops. Furthermore, transfer learning from pre-existing datasets provides a workable solution, making up for the lack of localised data by enabling pre-trained models to be adjusted for particular crops and illnesses.

4.2 Computational Resources

The computational demands of deep learning models present a hurdle, especially when deployed on low-power devices prevalent in developing countries. Implementing sophisticated models is further complicated by limited internet connectivity. Lightweight and effective deep learning models made especially for low-power devices are required to address this. Model compression and quantization techniques become crucial because they allow for the reduction of model size without sacrificing performance. This guarantees the efficient deployment and operation of disease detection algorithms on devices with constrained computational resources.

4.3 Deployment and Accessibility

When implementing deep learning-based technologies in rural areas, user-friendly applications and interfaces must be carefully considered. Limited technical literacy and language barriers can make it difficult to use these kinds of tools effectively. Developing user-friendly mobile applications with straightforward interfaces is essential to overcoming these obstacles and guaranteeing that farmers and local communities can easily utilise them. Language diversity should be taken into account when designing these applications, and support for multiple languages may be integrated. Furthermore, educational programmes are essential for improving technical literacy and guaranteeing that everyone in the community can benefit from deep learning for disease detection.

As deep learning technology develops, resolving these issues is critical to its successful application in resource-constrained agricultural environments. The transformative potential of deep learning in disease detection can be realised by emphasising novel approaches like smartphone-based imaging, lightweight models, and intuitive interfaces. This strategy has the potential to support resilient and sustainable farming methods in developing nations, resulting in increased crop yields and stable economies.

5 Summary & Conclusion

1. The conclusion summarizes the key findings of the review in general terms. Notable commonalities between works, whether favourable or not, may be included here.

2. This section is the reviewer's opportunity to justify a research proposal. Therefore, the idea should be clearly re-stated and supported according to the findings of the review.

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