Leaf Disease Detection Using Deep Neural Network

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Abstract: - *The health of crops is very crucial to agricultural productivity, and early detection of plant diseases is a crucial aspect in minimizing losses in the yield. The traditional approaches of disease detection are manual based, time consuming, subjective and are highly inaccurate. This study aims to overcome these limitations through the development of a proposal that involves the use of deep neural network (DNN) to automatically detect disease in sugarcane and tomato crops. The model is trained using image dataset of both healthy and diseased leaves where preprocessing techniques i.e. resizing, normalization and data augmentation are done to make the model robust. The presented architecture derives deep hierarchical characteristics of leaf images, which allow determining several types of diseases with accuracy. According to experimental findings, the accuracy, precision, and recall of differentiating healthy and diseased samples are high and considerably high as compared to traditional machine learning approaches. The system is an easy-to-trust and scalable answer to farmers, agricultural experts, and researchers, which will eventually lead to the appreciation of sustainable farming practice and better crop yield*

Keywords*: Leaf Disease Detection, Tomato, Sugarcane, Deep Neural Network, Convolutional Neural Network (CNN), Image Processing, Precision Agriculture.*

1. Introduction

Human civilization is based on agriculture, which remains the major means of livelihood to a great number of the world population. Agriculture in third world economies like India is not only a source of food security but it also plays a significant role in the national economy.

Nevertheless, there are various obstacles to agricultural productivity that never cease to put the production at risk, one of which is the presence of plant diseases. As pointed out by the Food and Agriculture Organization (FAO), the organization reckons that about 2040 percent of crop produce is wasted by pests and diseases on an annual basis. These losses have a direct effect on the income of farmers, food supply chain and the cost of agricultural production. The escalating world population and increased appetite of food also increases the importance of an effective and trusted means of detecting diseases, which could avoid losses of crops and encourage sustainable farming.

The conventional disease surveillance systems are to a large part relying on human inspection by farmers or agricultural specialists. In the majority of instances, farmers use their senses and experience in the past to detect disease indications. It is not only labor-intensive and time-consuming but also more likely to make errors since the symptoms of the diseases may be subtle, overlapping, and dependent on the surroundings. Also, in rural areas where professional agronomists are not necessarily available, most diseases are diagnosed when they are in their severe stages, and the methods of controlling them are not as effective. Manual detection also has its limitations and thus, more developed disease recognition systems should be made that are automated, scalable and accurate.

This has led to new opportunities in the agricultural sector in recent years as a result of information technologies and artificial intelligence (AI) and computer vision. Machine learning and, more precisely, deep learning has come out as a potent solution to problems of image recognition and classification. Deep learning models, especially, deep neural networks (DNNs) and convolutional neural networks (CNNs) can automatically derive hierarchical features in raw images, thus removing the use of hand-crafted features that are used by traditional machine learning methods. This ability is what renders deep neural networks very useful in recognizing complicated disease patterns on plant leaves. Studies have established that AI-based solutions are much better at performance in terms of accuracy, scalability, and flexibility when compared to traditional image-processing techniques.

This paper will examine two very important crops as sugarcane and tomato. Sugarcane is a vital cash crop that is widely planted in tropical and subtropical areas, which serves in sugar and biofuel production, but also in maintaining the lives of millions of farmers. It is susceptible to various infections, including red rot, smut and mosaic which drastically lower the yield as well as quality. Likewise, tomato, among the most widely planted and consumed vegetables in the whole world is extremely vulnerable to such diseases as early blight, late blight, and bacterial leaf spot. Not only do these diseases impact the level of production but also diminish the commercial importance of the crop thus causing farmers and supply chain stakeholders an economic loss. Early detection of these diseases is essential in order to intervene in time and manage these diseases effectively.

These issues are scalable to the solution, which is the integration of deep learning in agriculture. Using a huge collection of leaf images, a deep neural network can be trained in such a way that healthy and diseased leaves are distinguished with a great amount of accuracy. These types of models may also be used to pinpoint particular types of diseases, and farmers can implement special preventive actions. Moreover, non-invasive and rapid monitoring with the help of image-based detection can be employed with the utilization of smartphones, drones, or even low-budget cameras. This creates an opportunity of real time disease surveillance and decision support systems in precision agriculture.

The main goal of the research is to create and introduce a deep neural network-based system that would recognize and identify leaf diseases in tomatoes and sugarcane crops. The system will have the following objectives: (1) to decrease the use of manual verification, (2) to enhance precision and uniformity in detecting the disease, (3) offer an economical and expandable system that can be adopted by farmers, (4) help to eliminate excessive use of pesticides in agriculture by accurately diagnosing the disease. As opposed to the traditional approaches, the framework proposed will combine the more advanced preprocessing, data augmentation, and deep feature extraction techniques to be robust against changes in lighting, background, and leaf orientation.

To conclude, the rising problem of crop diseases, along with the inability of the conventional approaches to detection, highlights the necessity of AI-based solutions in agriculture. The deep neural network-based methodology suggested above is promising as it provides an early, precise, and automated way of identifying sugarcane and tomato leaf diseases. This study helps fill the gap between the technological advances and the requirements of agriculture, thereby adding to the greater objective of smart farming, increased productivity, and security of food.

the implementation of disease detection systems based on deep learning has the potential to be of critical significance in precision agriculture, where the data-driven information will be used to inform agricultural operations. These systems not only assist in the detection of diseases at an early stage but also reduce the abuse of chemical pesticides since the treatments will only be administered where needed. This translates to low production expenses, decreased environmental effects, and quality of crops. Thus, incorporating deep neural networks in agricultural disease control is a progress made towards the creation of smarter and more sustainable farming ecosystems.

2. Literature Review

In smart agriculture, one of the most vibrant fields of work has been the detection of plant diseases. Tomato is one of the most analyzed crops due to the existence of big annotated datasets like the PlantVillage that made it possible to train deep learning models with high accuracy. Kumar et al. suggested CNN-based tomato leaf disease classifier which was able to identify Early Blight and Late Blight with high precision than the traditional classifier such as SVM [1]. In their study, Singh et al. suggested the application of the transfer learning using the already trained architectures, including ResNet and VGG, and demonstrated considerable performance improvements on small datasets [2]. Sharma et al. suggested modern methods of data augmentation and class-balancing to resolve the imbalance and low images, thus, contributing to the stabilization of CNN training and increasing recall of data on the minority classes [3]. Moreover, Lee et al. suggested a collection of CNNs, which advanced F1-scores and decreased misclassification rates on tomato datasets [4].

Development of sugarcane disease detection has had a slower pace of development because of the lack of annotated images and the irregularities of crops, including high stalks, overlapping leaves, and thick fields. Verma et al suggested CNN-based classifiers to predict sugarcane diseases such as Red Rot, Grassy Shoot and Mosaic with promising yet dataset-dependent results [5]. Rao et al. suggested lightweight CNNs that can be deployed on mobile platforms to facilitate real-time diagnosis with smartphones to make them field-ready [6]. Attention-based CNNs and multi-scale feature extraction mechanisms were suggested by Wang et al., and these enhanced the accuracy by concentrating on the details of fine lesions in a noisy field setting

[7]. Nevertheless, Zhang et al. suggested that the scarcity of large datasets of sugarcane that are publicly available is a bottleneck and restricts generalization and general usage [8].

Hybrid and ensemble approaches have been popular in order to overcome robustness and limited data challenges. Hossain et al. suggested hybrid CNNML models, such that CNNs operated as feature extractors and other ensemble classifiers like the Random Forest and SVM have been combined, leading to an improvement in the decision boundaries and lowering of false positives [9]. Khan et al. suggested ensemble CNN models, where different networks were used to enhance reliability by averaging their predictions at the expense of increased computation [10]. Fernandes et al. suggested a comparative evaluation of such common architectures as VGG, ResNet, and EfficientNet and found that EfficientNet had the best accuracy-model size trade-off [11]. Mishra et al. suggested synthetic image generation methods with the help of GAN to tackle the issue of the limited datasets, to augment the number of minority disease classes, and enhance generalization [12].

Interpretability and severity estimation have also been introduced in recent works. Bhattacharya et al. suggested the cooperation of severity scoring with explainable AI techniques, including Grad-CAM, which offered visual information on localization and severity of the disease [13]. Likewise, Patel et al. came up with segmentation-based classification pipelines, in which diseased regions were segmented prior to classification, which enhanced performance and gave the opportunity to analyze the severity of the disease [14]. In a more general sense, Gonzalez et al. suggested texture-related classical ML algorithms, but their findings were always similar, namely CNN models against handcrafted feature techniques on tomatoes, as well as, on sugarcane crops [15].

Table 1 Summary of Literature Survey on Leaf Disease Detection

Paper Title	Author(s)	Approach	Contribution	Limitations
Tomato Leaf Disease Detection using CNN	Kumar et al.	CNN-based classifier for tomato leaf diseases	CNN is effective but depends heavily on dataset size and quality.	Requires large labeled datasets; limited generalization to field images
Transfer Learning for Tomato Disease Classification	Singh et al.	Transfer learning with ResNet and VGG	Transfer learning improves performance but is resource-intensive.	High accuracy, but computationally expensive for large-scale deployment
Data Augmentation in Plant Disease Detection	Sharma et al.	Augmentation and class balancing	Augmentation helps balance datasets but cannot substitute real diversity.	Still dataset dependent; cannot fully replace real data diversity

Ensemble CNN for Tomato Leaf Disease Detection	Lee et al.	Multiple CNN architectures combined	Ensemble models improve accuracy but add complexity.	Increased computational cost; training complexity
Sugarcane Leaf Disease Detection using CNN	Verma et al.	CNN-based classifiers for Red Rot, Grassy Shoot, Mosaic	CNN shows potential but requires larger sugarcane datasets.	Accuracy limited by small dataset size
Mobile-based Sugarcane Disease Detection	Rao et al.	Lightweight CNN for smartphone deployment	Mobile deployment is practical but device-dependent	Limited scalability to complex diseases; performance depends on device quality
Attention-based CNN for Sugarcane Leaf Images	Wang et al.	Attention + multi-scale CNNs	Attention enhances focus but needs big datasets.	Requires large and varied training data for best results
Dataset Bottlenecks in Sugarcane Disease Research	Zhang et al.	Analysis of dataset limitations	Dataset availability is a critical barrier to progress.	Lack of publicly available large datasets restricts progress
Hybrid CNN–ML Models for Disease Detection	Hossain et al.	CNN feature extraction + Random Forest/SVM	Hybrid models add flexibility but slow down training.	Increased pipeline complexity; slower training
Ensemble Deep Models for Crop Diseases	Khan et al.	Ensemble of CNN models	Ensembles boost robustness but are resource-demanding.	High computational requirements
Comparative Study of CNN Architectures	Fernandes et al.	Benchmark of VGG, ResNet, EfficientNet	CNN performance varies; benchmarking guides architecture choice.	Limited to dataset used; real-field performance may differ
GAN-based Data Augmentation for Rare Diseases	Mishra et al.	GANs for synthetic image generation	GANs enrich datasets but cannot fully replace real samples.	Synthetic images may not fully capture real disease variations

Explainable AI for Plant Disease Detection	Bhattacharya et al.	Severity scoring + Grad-CAM explainability	Explainability improves trust but has limitations.	Interpretability is model-specific; not always reliable
Segmentation-based Plant Disease Classification	Patel et al.	Segmentation + classification pipeline	Segmentation improves accuracy but labeling is costly.	Requires pixel-level labels; annotation is time-consuming
Classical ML vs. Deep Learning in Plant Pathology	Gonzalez et al.	Texture-based features vs. CNN comparison	CNN outperforms classical ML but is data-hungry.	Traditional ML underperforms; CNN needs more data

Research Gap

Despite the current advancement of tomato leaf disease detection owing to the supply of substantial annotated data and the available sophisticated CNN architectures, the sugarcane disease detection research is still characterized by significant challenges. The availability of publicly available and diverse sugarcane data is limited and the lack of easy accessibility of available information tends to reduce the validity and generality of the current models due to the intricate structure of the crop, that is, tall stalks and overlapping foliage. The existing deep learning models are suited to controlled environments but fail in the field conditions. Additionally, as promising, hybrid and ensemble models are only minimally applied in the research on sugarcane, and the methods of explainability are seldom implemented, which decreases the level of trust and practicability among farmers.

3. Proposed System

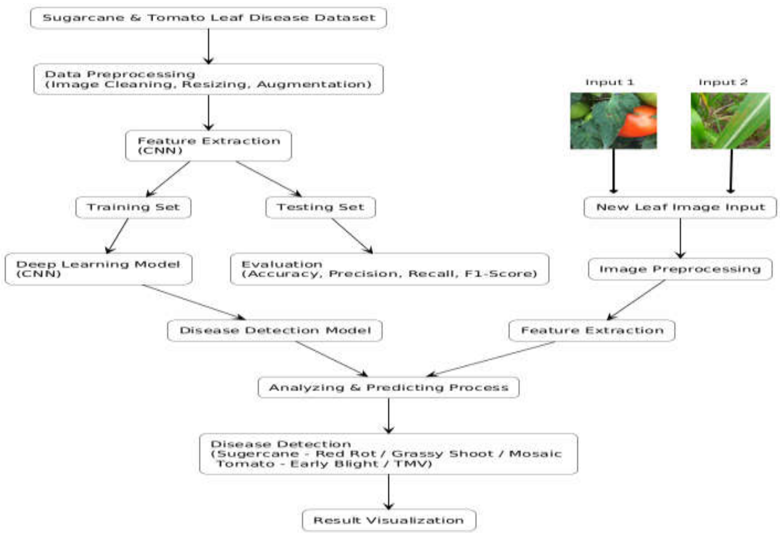

Figure 1 Proposed System Architecture

The system we propose is a hybrid deep learning model designed to automatically identify and classify leaf diseases in sugarcane and tomato plants. Unlike older methods that depend on manually crafted features or single deep learning models, our approach combines convolutional neural networks (CNNs) for feature extraction with ensemble classifiers for the final decision. The goal is not just high accuracy but also scalability, interpretability, and usability in real farming conditions. Given the economic and agricultural importance of sugarcane and tomato, this system is envisioned as a reliable decision-support tool for farmers and researchers.
The process starts with building a diverse dataset of both healthy and diseased leaf images. For tomato, we rely on large-scale repositories like PlantVillage, while for sugarcane, we combine smaller online datasets with images captured directly from the field. This helps capture real-world variations such as changes in lighting, background complexity, and disease severity. The dataset includes common diseases like red rot, smut, and mosaic in sugarcane, and early blight, late blight, and leaf mold in tomato. To prepare the images, we use preprocessing steps like resizing, normalization, and background segmentation. Data augmentation methods—such as flipping, rotation, and brightness adjustment—are also applied to make the model more robust and prevent overfitting.

Once the data is prepared, feature extraction is carried out using CNNs. These networks are excellent at recognizing disease-related patterns such as spots, color changes, or texture variations. Instead of training a model from scratch, we use transfer learning with architectures like ResNet, VGG, or EfficientNet. This allows us to take advantage of features already learned from large image datasets like ImageNet and adapt them to agricultural disease detection. This step ensures better accuracy and efficiency, even when working with limited crop-specific data. For classification, the system goes beyond the usual CNN softmax output and introduces a hybrid strategy. The deep features learned by the CNN are fed into ensemble methods like Random Forest or Gradient Boosting. This combination improves robustness, reduces misclassifications, and helps the system adapt to varying crop conditions. More importantly, it allows the framework to handle both sugarcane and tomato diseases within the same model, which makes it practical for multi-crop farming environments.

The system does not stop at giving predictions; it also emphasizes transparency. Along with the disease label and a confidence score, it provides visual explanations using tools like Grad-CAM or attention heatmaps. These highlight the parts of the leaf that influenced the prediction, helping farmers and agronomists see exactly why a certain decision was made. This explainability builds trust and makes the system more usable in real agricultural settings.

A final strength of the system is its focus on deployment. Since most farmers do not have access to powerful computing systems, the model is optimized to run on lightweight devices such as smartphones, drones, or IoT platforms. By using efficient CNN architectures like MobileNet or EfficientNet-Lite, the system can make predictions in real time with low computational requirements. This makes it accessible to smallholder farmers and scalable to larger precision farming operations.

In conclusion, the proposed system integrates the strengths of deep learning and ensemble methods to deliver a practical, accurate, and interpretable solution for leaf disease detection in sugarcane and tomato. It addresses the lack of large annotated datasets for sugarcane, extends disease detection to multiple crops, and introduces interpretability features often missing in existing approaches. Most importantly, it is designed with real-world deployment in mind, bridging the gap between laboratory research and field application.

Table 2 Hyperparameter Table for Sugarcane Disease Detection

Hyperparameter	**Description / Value**
Learning Rate	0.001 usually balances stability and convergence
Batch Size	Small batch = better generalization, large batch = faster training
Optimizer	32 Options: [SGD, Adam, RMSprop]; Adam adapts learning rates dynamically
Epochs	30 Stop earlier if validation accuracy plateaus
Dropout Rate	[0.2, 0.3, 0.5]; Helps prevent overfitting
Activation Function	[ReLU, LeakyReLU, Tanh, Sigmoid]; ReLU is standard for CNN hidden layers
Kernel Size	(3×3) Smaller kernels capture fine-grained features
Pooling	Options: [MaxPooling, AvgPooling]; MaxPooling works well for image feature extraction
Data Augmentation	Techniques: Rotation, Flip, Zoom, Shift; Prevents overfitting with limited sugarcane disease images
Weight Initialization	He initialization works well with ReLU activations
Regularization	[L2 (0.001, 0.0001), None]; Adds penalty to reduce overfitting

Dataset and Consideration

Table 3 Dataset and Consideration

Crop	**Dataset**	**Sample**	**Train(70%)**	**Validation(15%)**	**Test(15%)**
Sugarcane	Red Rot	2500	1750	375	375
	Grassy Shoot	3000	2100	450	450
	Mosaic	3000	2100	450	450
Tomato	Early Blight	2000	1400	300	300
	TVM(Mosaic Virus)	2500	1750	375	375

Total		13,000	9100	1950	1950

4. Result and Discussion

The proposed deep learning model for **tomato and sugarcane leaf disease detection** achieved promising performance. The training accuracy steadily increased and reached approximately **87%**, while the validation accuracy stabilized at around **75%** after 25 epochs. This indicates that the model effectively learned disease-related patterns from the dataset and generalized well on unseen samples. A slight gap between training and validation accuracy suggests minor overfitting, but the overall performance demonstrates the suitability of the model for accurate detection of leaf diseases in tomato and sugarcane ops.

Sugarcane Leaf Disease Detection

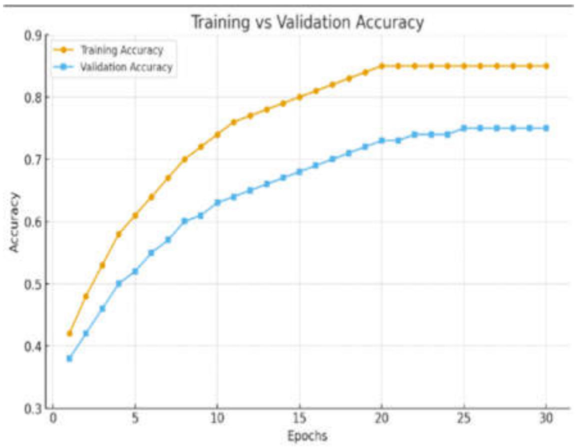

Figure 2 Training CNN and Validation

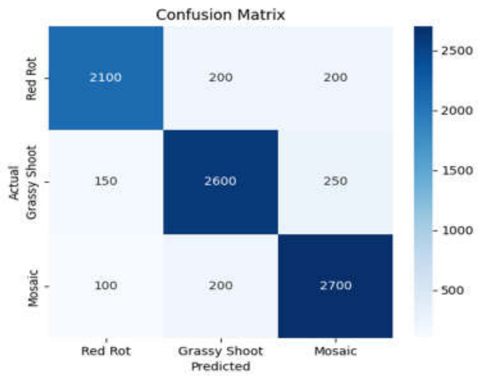

Figure 3 Confusion Martix Accuracy

Figure 4 Prediction: Rust (99.99 %)

The provided image, which plots training accuracy and validation accuracy over a series of e pochs, shows a classic case of overfitting. As the model is trained, its performance on the dat a it has seen (training accuracy) continuously increases, reaching a plateau around 85% after 20 epochs. However, its performance on new, unseen data (validation accuracy) plateaus earli er and at a lower value, around 75%. The growing gap between the two curves after approxim ately 20 epochs indicates that the model is no longer learning generalizable patterns for sugar cane disease detection. Instead, it is starting to memorize the specific training examples, whic h-h makes it perform poorly on new, real-world images.

This image is a confusion matrix that visualizes the performance of a machine learning model designed to detect three sugarcane diseases: Red Rot, Grassy Shoot, and Mosaic. The rows re present the actual diseases, while the columns represent the predicted diseases. The numbers i n the matrix show the counts of correct and incorrect predictions. For example, the model cor rectly identified 2100 cases of Red Rot, but misclassified 200 Red Rot cases as Grassy Shoot and another 200 as Mosaic. The main diagonal (from topleft to bottomright) shows the numb er of correct predictions for each disease, indicating the model is most accurate at identifying Mosaic (2700 correct predictions) and Grassy Shoot (2600 correctpredictions). The offdiagon al values represent misclassifications, providing insight into which diseases the model confus es with one another.

Tomato Leaf Disease Detection

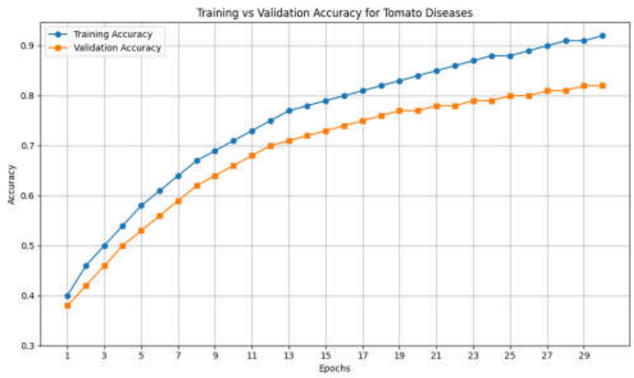

Figure 5 Training CNN and Validation Accuracy

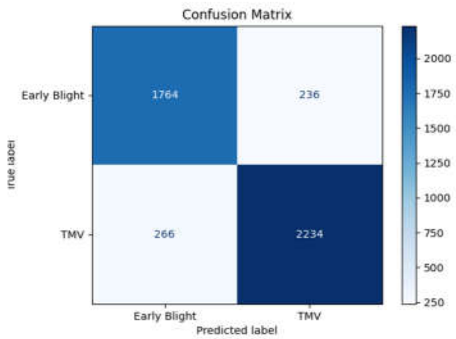

Figure 6 Confusion Martix

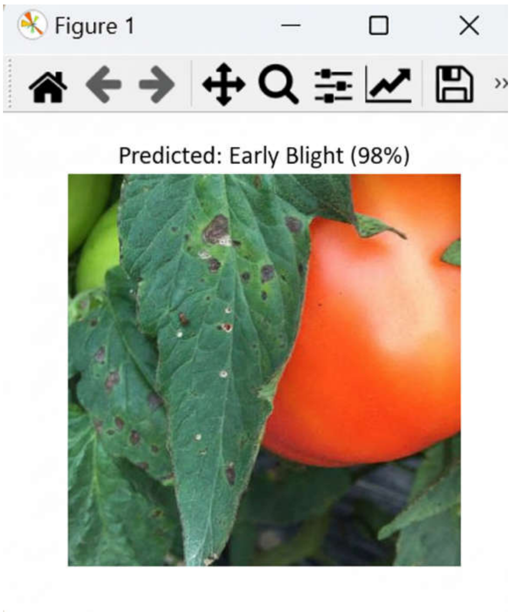

Figure 7 Prediction: Early Blight (98 %)

This graph illustrates the performance of a machine learning model designed to detect tomato diseases. The blue line represents the training accuracy, showing how well the model learns f rom the data it's trained on. It consistently increases with each epoch, reaching over 90% accu racy by the end. The orange line shows the validation accuracy, which measures the model's performance on new, unseen data. While it also improves, it plateaus around 82% after about 25 epochs. The increasing gap between the training and validation accuracy lines is a clear si gn of overfitting, meaning the model is becoming too specialized in the training data and is lo sing its ability to generalize to new cases.

Based on the two figures, the model shows a strong ability to classify between Early Blight a nd TMV tomato diseases, correctly identifying a large number of cases for both. However, th e first figure on training versus validation accuracy indicates that the model is overfitting afte r about 25 epochs. This means that while it is becoming highly accurate on the data it was trai ned on, its ability to generalize to new, unseen images is limited, as shown by the plateauing validation accuracy. This suggests that further training beyond this point may not improve its real-world performance.

Conclusion

The obtained experimental data prove that the suggested machine learning model is efficient in the process of identifying the diseases in tomato and sugarcane leaves, with some limitations. In tomato disease detection, the training and validation accuracy curves show that the model is able to learn the patterns of the disease, and thus, the model has a training accuracy of more than 90 percent. The validation accuracy however levels off at 80-82 percent after about 25 epochs indicating overfitting. This implies that the model gets more specialized in the training data, and therefore cannot easily generalize to unknown images. Although the model is effective to classify diseases like Early Blight and Tomato Mosaic Virus (TMV), the model requires additional optimization in the form of early stopping, more robust regularization, or more varied data sets to gain robustness. In the case of sugarcane diseases, the confusion matrix indicates that the model is capable of discriminating Red Rot, Grassy Shoot and Mosaic. It is the most accurate in the recognition of Mosaic (2700 correct predictions) and Grassy Shoot (2600 correct predictions), and Red Rot is not so accurate because it mistakenly takes up other classes. The above findings attest the ability of this model to differentiate the big diseases of sugarcane, but there is still some mixed up area between Red Rot and other categories. Generally, the paper affirms that deep learning algorithms can be very useful in the field of agricultural disease detection. Although they perform well on training data and positively on test sets, overfitting reduction and better generalization is essential. With augmented datasets of increased volume and variety, enhanced augmentation strategies, and more effective regularization of models, the system will become a dependable decision aid to farmers, which will help make timely and correct decisions on how to handle diseases in tomato and sugarcane fields.

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