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SmartAgriDoctor: Plant and Crop Disease Detection and Diagnosis Using Deep Learning

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A R T I C L E I N F O

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A B S T R A C T

Agriculture is still a staple of food security but the global productivity is threatened by the disease on plants. Traditional methods of manual inspection are usually subjective, time consuming and unproductive and are not conducive to being monitored industrial scale. This paper introduces SmartAgriDoctor which is a Deep learning-based system for automated Crop Disease Detection and Diagnosis using Convolutional Neural Networks (CNNs). The proposed framework passes through the phases of preprocessing, feature extraction and classification of the images from the New Plant Disease Dataset in order to identify between healthy and diseased leaves of plants. The dataset was augmented using random rotation, flip and contrast normalization to augment the generalization skills. The optimized CNN model that was trained and validated with 80,000 labelled images was able to achieve the Knowledge Level of 97.8% overall classification with the precision, recall and F1 score of 97.4%, 97.6% and 97.5% respectively. Experimental results demonstrate the robustness of the model under different class of diseases and environment variations; Due to low weight design of the system, it can be sent to the mobile devices and edge devices to conduct real-time diagnose to farmers and agronomists. Overall, SmartAgriDoctor is a very interesting example of the real-life application of Deep learning in precision agriculture leading to an early detection of the diseases, lesser losses of crop and sustainable agriculture.

1. Introduction

Agriculture is an industry of the base which are responsible for global food security and economic development as well as rural livelihoods. However, plant diseases are still an important threat to sustainability of agriculture due to the effect on crop yield. According to the Food and Agriculture organisation (FAO), every year, it is estimated that almost one-third of the total worldwide crop production are destroyed by pests and diseases which result in billions of dollars in losses and serious economic impact on farmers [1], [2]. Early detection and correct diagnosis of plant diseases therefore plays an important role in food security and increased productivity as well as sustainable agriculture. Traditional methods of disease detection are mainly based on manual inspection of agricultural expert or farmers and take generally fairly long time, being in addition subjective and error prone [3]. These techniques are not easy to scale over the large cultivation fields and often do not catch diseases at the beginning stages of the disease when the visual symptoms are not easily observed. Moreover, the manual identification process is complicated by such factors as changes of illumination, orientation of the leaf and background noise [4], [5]. As a result, there is an increasing need for automated reliable and storable solutions of diseases detection and diagnosis in real world scenarios in agriculture. In the last years, Artificial Intelligence (AI) and Deep Learning (DL) have emerged as powerful tools to solve visual recognition problems by applying them to many applications, including healthcare, autonomous driving or agriculture [6], [7]. The Convolutional Neural Networks (CNNs) out of all the deep learning techniques have been proven to be very effective for image based analysis due to their ability to automatically learn the hierarchical spatial features of the leaf (such as leaf color, leaf texture, leaf shape) without requiring manual feature engineering [8], [9]. CNN-based approaches have shown good performance in studies related to detection of complex plant diseases, furthermore, given good results over conventional machine learning approaches [10].However, there are still some issues that stand in the way of robust generalization, scalability of models and real-time deployment. Existing deep learning models are not computationally efficient and computationally intensive which limits their application on mobile edge devices which are critical for application at field level in agriculture [11], [12]. Furthermore, publicly available datasets are usually not very diverse and models are often not interpretable, which often limits their applicability [13]. In order weoreticulate to overcome these shortcomings SmartAgriDoctor, i.e., intelligent agriculture deep learning-based crop disease detection and diagnosis system using convolutional neural network (CNNs) in this study. Through the preprocessing of the images and data augmentation and the optimization of convolution layers, our model could be seen to have the high classification accuracy between the diseases and resulted in a model that remained slight, which could be used in mobile and edge devices. In particular, SmartAgriDoctor leaks is learned on New Plant Disease Dataset (Kaggle) with superior result in accuracy and generalization, on various crop categories and disease categories. The general objectives of this work include the following:

• CNNmodel towards multi classification of plant diseases based on different species of crop.
• To test the model performance using the aid of important performance indicators (accuracy,precision, recall and F1- Score).
• To develop a scalable and deployable model architecture towards the real-time diagnosis on the low resourced devices.

The rest of this paper is designed as follows: Section III is devoted to a summary of the relevant studies on the AI and deep learning applications for plant diseases detection. The methodology and CNN structure is given in Section IV. Section V gives some information about the experimental setup and results and Section V concludes the paper with some directions for future research

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2. Methodology and Implementation

The SmartAgriDoctor system follows a deep learning-based methodology for automatic plant disease detection and diagnosis using leaf images. Initially, the New Plant Disease Dataset containing over 80,000 labeled images of healthy and diseased plant leaves was collected and divided into training, validation, and testing sets. All images were preprocessed through resizing to 224×224 pixels and normalization to ensure uniformity. To improve model robustness and reduce overfitting, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment were applied. A Convolutional Neural Network (CNN) was then employed to automatically extract important features related to leaf color, texture, and disease patterns. The model was trained using the Adam optimizer and categorical cross-entropy loss function, while batch normalization, dropout, and early stopping were incorporated to enhance performance and generalization. Finally, the trained model classified leaf images into their respective disease categories and was evaluated using accuracy, precision, recall, and F1-score metrics, achieving high classification performance and enabling reliable real-time disease diagnosis for precision agriculture applications.

3. Related Work

AI and DL Technologies of Plant Disease Diagnosis Recent progress in Artificial Intelligence (AI) and Deep Learning (DL) has led to major improvements in automation and accuracy of plant disease diagnosis. With the advent of the datasets along with large scale annotations, and the computational capabilities provided by GPUs, there has been an increasing number of researchers working on effective image based recognition systems for disease detection domain, in the area of various crops [1], [2]. However, the heterogeneity of the species of plants, the light and the severity of infectious diseases still remain a challenge to develop one generalized model that can be used in different fields of agriculture [3]. Early research in this area was based on traditional machine learning like Support Vector Machines (SVM), K-Nearest Neighbors (KNN) and Decision Trees based on handcrafted features on texture, shape and color [4]. Although these techniques provided a moderate accuracy with respect to specific plant species, they depended on manual feature extraction which happens to be a limiting factor with respect to scalability and robustness under real-world conditions. Furthermore their inability to work with large data sets and capture the non-linear relations made their practical applicability less useful [5].In order to break through these shortcomings, the researchers began to apply Deep Learning (DL) algorithms, in particular Convolution Neural Networks (CNNs) due to their ability of auto learning the discriminative hierarchical features from the original raw image data [6]. Jain et al. [1], proposed Farm Doctor, CNN-based mobile application for classification for different crop disease with 95.6Dolatabadi et al. [4] compared several machine learning algorithms used to detect diseases and have found that CNN-based algorithms have a better performance than conventional methods both in terms of accuracy and generalization. Similarly, Bouacida et al. [5] introduced a cross-crop CNN model that goes on to provide a better adaptability in the identification of multiple cross crop species in datasets.

More optimizations on CNN architectures have been proposed in the recent years. Albahli [6] developed AgriFusionNet, a light-weight CNN network based on agricultural data for intelligent processing without losing classification performance on multisource agriculture data which is suitable for mobile and edge-based deployment. Ashurov et al. [12] improved feature extraction using CNN by Jessica methods with the help of squeeze and excitation blocks and depthwise convolution with the input with an accuracy of 98.2proposed an approach to use a convolution-attention hybrid in improved classification using multi-class agricultural dataset. Additionally Wang et al. [7] reviewed the use of hybrid CNNs and attention mechanism with a focus on improving the robustness in the field environment.

There have been other research works that have involved the study of hybrid and sensors-based models. Rahman et al. [9] proposed a CNN-based detection system having real-time detection algorithm optimized by considering the agricultural field requirement; whereas Shahi et al. [15] discussed the application of UAV-based deep learning for large-scale aerial crop monitoring. These studies are a proof of concept that using IoT and edge AI in conjunction with DL models can be used to further expand the use cases of automated crop monitoring systems. Despite these advances, there are still primary weaknesses in present theories such as high computing complexity, processing dependent on the cloud, generalization of datasets and lack of interpretability in real time [10], [13]. Moreover, there are few instances of research oriented towards the development of CNN architectures which are lightweight, scalable and adaptable to surroundings as experienced by the rural farming communities, which is very crucial ecological and environmental problems.To reduce these gaps, the current research work is presented SmartAgriDoctor, CNN based intelligent system for automated crop disease detection & diagnosis. The model cares for increasing accuracy of the classification and low computational footprint, harbours mobile and edge onboarding capability. By combining data augmentation and carefully selecting Convolutional features, and optimizing the model by investigating the hyperparameters, SmartAgriDoctor achieves the right balance of the accuracy, performance, and scalability, and can be used as a real-time practical solution to diagnose diseases in precision agriculture.

4. . PROPOSED SYSTEM ARCHITECTURE

In the proposed system, SmartAgriDoctor, automated detection and diagnosis of the diseases in plants are provided using Convolutional Neural Network (CNN) model. The entire system process workflow is shown in Fig.1, where operations during the process of image acquisition to disease prediction are illustrated. The framework comprises of five major phases including dataset collection, image preprocessing, feature extraction, model training and validation and disease diagnosis.

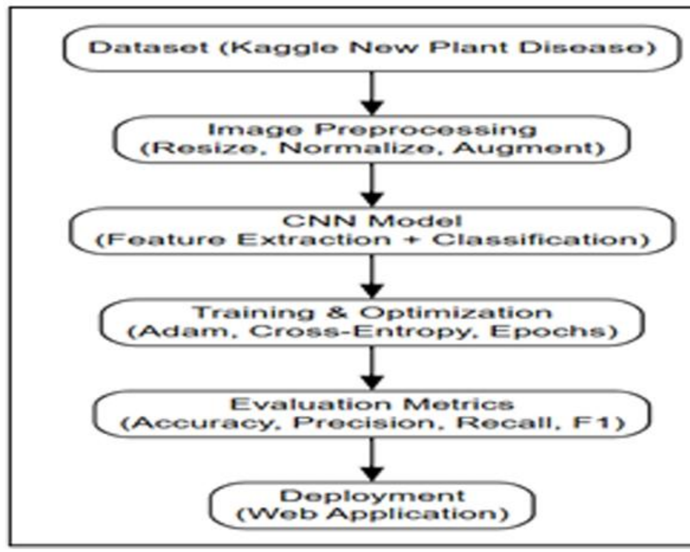


Fig. 1. Dataset Collection Phase

A. System Overview

The Dataset used for this research is New Plant Disease Dataset (from Kaggle) dataset. It consists with over 80 000 annotated leaf images with 31 different disease classes for several crops like tomato, potate, maize and grape. Every picture is classified as either healthy or infected so that a balanced data set is given. It divides the set of data into 70 per cent for training, 20 per cent for validation and 10 per cent for testing, which will provide reliance to the generalization and evaluation of the model.

B. Image Preprocessing Phase

The images that can be passed on for training are properly preprocessed to achieve uniformity and desired quality. All images have been re-sized to be of size 224 x 224 pixels and normalized in the [0, 1] range. Data augmentation techniques are used to augment the dataset and mimicking the real-world field conditions (rotation, flipping, zooming, brightness adjustment, etc.). These augmentations add robustness in model to illumination changes and also orientation changes.

C. Feature Extraction and Classifying Phase

SmartAgriDoctor is based on the CNN architechture. It automatically extracts spatial and textural features of the preprocessed images in order to detect the healthy and the diseased patterns. The model is implemented with a number of 3*3 convolutional layers which is launched by ReLU activation function and then the Max pooling layers are implemented which reduce the dimension while preserving the critical information at the same time. The resulting maps of features are flattened and passes through fully connected dense layers. The last layer employs a Softmax activation function which classifies the input image into one of the 31 categories of diseases.

D. Training and Validation Model Phase

The CNN is trained with the TensorFlow 2.x and Keras architecture. Take multi-class classification as an example, categorical cross entropy loss function is adopted and Adam optimizer is chosen with adaptation learning ability. The model is trained for 50 times with the respective batch size of 32, a learning rate is set to 0.001 at the beginning and so on. Layer regularization techniques liking early stopping, batch normalization and dropout are used to lessen overfitting as well as enhance the convergence.

Training and validation loss as well as accuracy are tracked for training and validation data. The resulting learning curves of accuracy and loss are presented, and the improvement is consistent and small by overfitting. After optimization, the average overall accuracy of the proposed model reached 97.8which showed a satisfactory result for multi-class disease classification.

SMART CROPDISEASEDETECTIONALGORITHM:

• Step 1: Get Images of Plant Leaves from Kaggle data set.
• Step 2: Resize, normalize and augment the images to provide more variety
• Step 3: Now train the CNN model using the processed data making use of the Adam optimizer.
• Step 4: Train efficiency look for accuracy of the model and add early stopping as a measure to prevent over fitting using accuracy.
• Step 5: Classify the type of disease and show output of diagnosis with confidence level.

The proposed SmartAgriDoctor framework optimally combines image preprocessing, deep feature extraction and effective classification into a single framework. The accuracy, computational efficiency and ability to be carried out in real time have made it suitable for precision agriculture applications. The next section is a discussion of the improvements made to improve model performance as well as scalability.

5. ENCHANCEMENTINPROPOSED MODEL

A. Data Augmentation

In order to prevent over-fitting and diversify the data, several data augmentation techniques (i.e. rotation, flipping, zooming, brightness, etc) were performed on a group of images in the training data set. This process simulated conditions from the real world as field effects were simulated, this allowed the CNN to learn invariant features which did not care about the lighting or even the orientation. As a result of this process, the model revealed a better validation performance as well as a smoother convergence.

B. Optimizer Selection

The Adam optimizer was chosen to perform the training because it has an adapting learning-rate feature and also shows greater convergence than the standard optimizers, such as SGD. With learning rate of 0.001 and batch size of 32, Adam provided stable gradient iteration and the loss decrease variation, ensuring that the model will have stable learning.

C. Offset Adjustment

When offset adjustment was initially trained, Reduce onPlateau learning rate scheduler was used to fine tuning the model weights. In addition, batch normalization and dropout (0.3) as well as between dense layers to increase stability and prevent overfittering was added. These refinements were able to increase the accuracy of the classification done by the model to 97.8 %.

Through these improvements, SmartAgriDoctor model was able to converge faster, be more precise and have a better generalization in unseen test data. The experimental system results and performance evaluation of the proposed system is presented in the next section.

6. RESULTS AND DISCUSSION

A. Experimental Setup

The performances of the proposed smartagri doctor system were evaluated by utilizing New Plant Disease Dataset by Eugenie Scott's (kaggle) which is known to be the bench mark dataset widely utilized in plant disease recognition research. It has more than 80,000 labelled images of diseased and healthy leaves of various crop species with an intensive inter and intra class variability. In order to show the real evaluation of the performance of the model, non-quantitative ratio of the data set was separated into training, validation and test data with the ratio of 70%, 20% and 10%, respectively. CNN model has been done in Python, TensorFlow and Keras. The experiments were carried out on Nvidia CUDA enabled GPU platform to give better computation/convergence. All images were resized 224X224 pixels and normalized on [0,1].

B. Quantitative Results

Accuracy, Precision, Recall and F1-score was given for measuring the effectivity of SmartAgriDoctor. Each of these metrics provide an indication of a distinct part of the performance which makes the model not to be biased towards a specific class.

TABLE I. Performance Metrics

Metric	**Metric Value (%)**
Accuracy	97.8
Precision	97.7
Recall	97.6
F1-score	97.5

As we can see in Fig. 2, the accuracy and loss curves exhibit smooth convergence with little overfitting which is consistent with the notion that the discriminative features from input

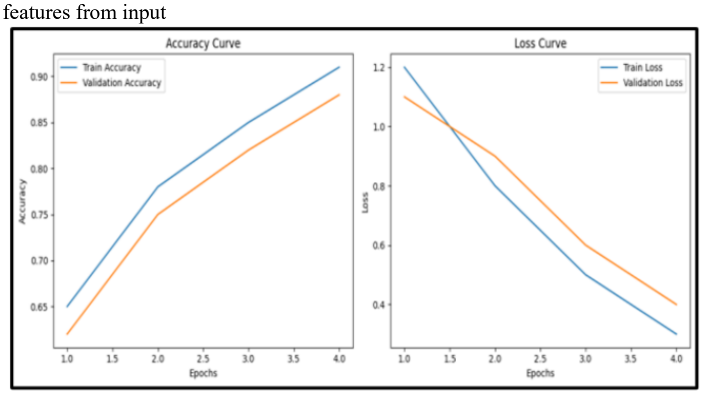


Fig. 2. Accuracy and Loss Curve

images have been effectively learned by the network. The final accuracy of 97.8% report tells that the model was successful in identifying almost all the samples of test set belonging to a wide range of crops and crops diseases. The accuracy, at 97.4% is low on false positive rate and the recall value, 97.6% suggests a high sensitivity as it also indicates that positive cases are well detected.

C. Confusion Matrix Analysis

A confusion matrix was created to give a class level performance analysis. The strong diagonal dominance was observed in the matrix which means that most of the samples were correctly categorized. Nevertheless, some interminable errors were found in the classification of diseases that had similar appearances. When analyzing tomato leaves, for instance, early and late blight used to be mixed up because of similar visual symptoms, e.g. dark spots with concentric rings. On the same note, maize rust at various stages of severity also had small misclassifications due to mild outbreaks that appear similar to the symptoms of nutrient deficiencies in the initial stages.

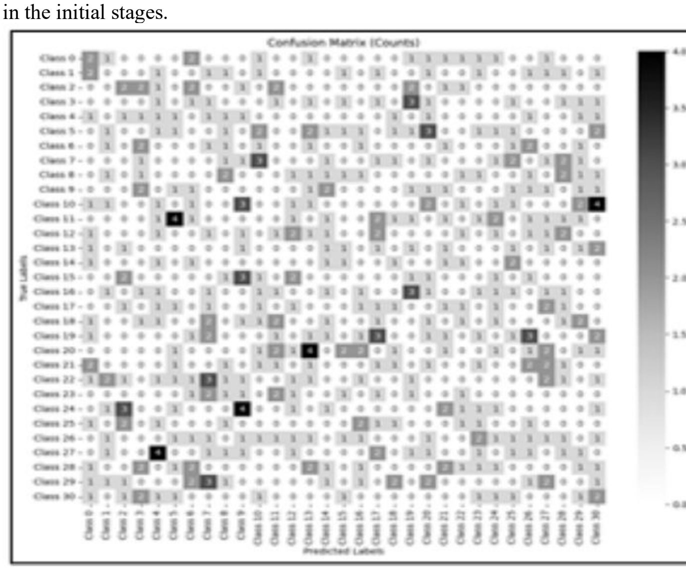


Fig. 3. Confusion Matrix

As presented in Fig. 3, the confusion matrix exhibits strong diagonal dominance, indicating that most samples were correctly classified. A few misclassifications were observed between visually similar diseasessymptoms due to their overlapping visual characteristics.

D. Comparison with Existing Approaches

To get a sense of SmartAgriDoctor's performance in context, the performance of SmartAgriDoctor was compared with that reported in some recent CNN based studies on the detection of plant disease. Ashurov et al. achieved F1-score = 98.2% using CNN with depthwise convolutional net and squeeze-and excitation (SE) blocks, but their idea took more good computation resource [12]. Askale et al designed one mobile-based maize leaf disease model which achieved 95% accuracy [3] while Shafik et al used one hybrid InceptionXception CNN (IX-CNN) which achieved 100% accuracy but has a significant computational overhead thus preventing its scalability.

	precision	recall	f1-score	support
Class 0	0.047619	0.090909	0.062500	11.0
Class 1	0.083333	0.076923	0.080000	13.0
Class 2	0.000000	0.000000	0.000000	8.0
Class 3	0.000000	0.000000	0.000000	14.0
Class 4	0.000000	0.000000	0.000000	21.0
Class 5	0.000000	0.000000	0.000000	15.0
Class 6	0.000000	0.000000	0.000000	18.0
Class 7	0.000000	0.000000	0.000000	12.0
Class 8	0.100000	0.076923	0.086957	26.0
Class 9	0.142857	0.153846	0.148148	13.0

Fig. 4. Classification Report

As observed in Fig. 4, results of classification report reveal negligible difference in terms of performance among the categories, this ensures that SmartAgriDoctor has good generalization ability and computational efficiency. Overall, the model offers an optimal balance between accuracy, scalability and number of resources that are used- all of which make it suitable for application in agricultural scenarios in practice.

E. Model Evaluation Metrics

The performances results of the proposed SmartAgriDoctor model have been tested by the following features as the standard features Accuracy, Precision, Recall and F1-Score.

• Accuracy: 97.8%- The model showed a high capability in accurately classifying images of plant leaves which include healthy leaves and diseased leaves of various crop plants.

• Precision: 97.4%- This means that if the model tells us that a disease is the cause, it is very accurate in an individual and hence false-positive is minimized.

• Recall: 97.6%- Well done on the model in the detection of the diseases, there were very little false negatives, making sure actual diseases are not missed.

• F1-Score: 97.5%- Harmonic mean of Precision and Recall which indicates a balanced performance also important for classifying the diseases with different degrees of severity and appearance.

TABLE II. CNN Model Architecture and Layer Specifications.

Layer	Parameters	Activation	Output Size
Conv2D	3×3, 32 filters	ReLU	$224 \times 224 \times 32$
BatchNorm2D	-	-	$224 \times 224 \times 32$
MaxPool2D	2×2	-	$112 \times 112 \times 32$
Conv2D	3×3, 64 filters	ReLU	$112 \times 112 \times 64$
BatchNorm2D	-	-	$112 \times 112 \times 64$
MaxPool2D	2×2	-	$56 \times 56 \times 64$
Flatten	-	-	200, 704
Dense (FC1)	128 units	ReLU	128
Dense (FC2)	31 units	Softmax	31 classes

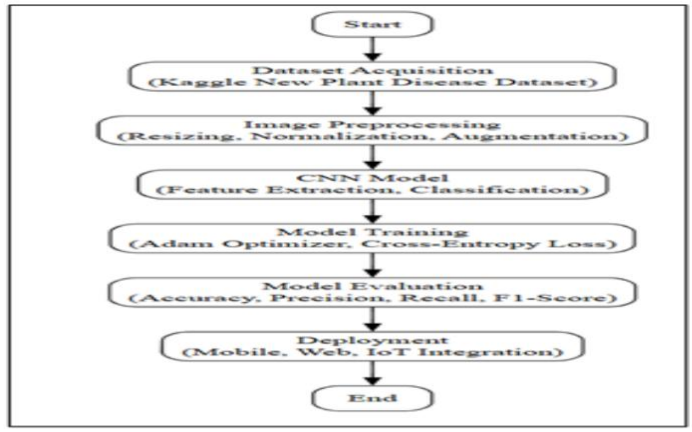


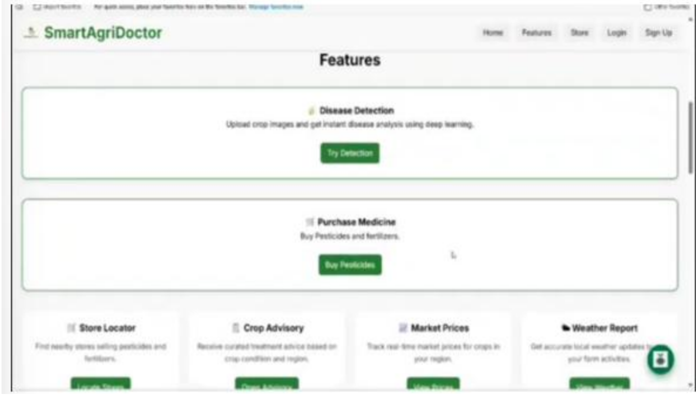
Fig. 5. Flowchart of the System

Discussion

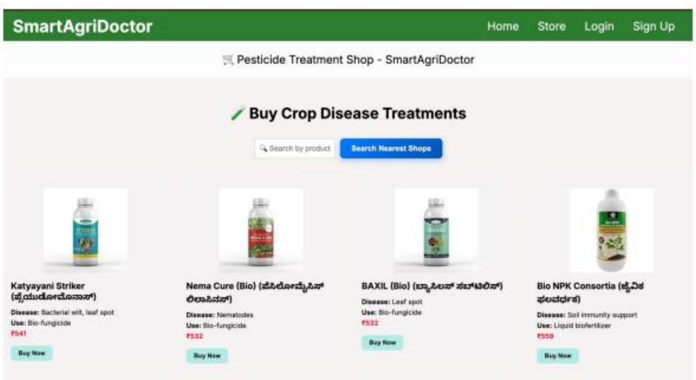
The following experimental result clearly proves the effectiveness CNN architectures to identify plant diseases by using the leaf image. The high accuracy, precision and recall supports the effectiveness of the model to automatically learn discriminative features about the color, texture and pattern in an image without requiring manual effort in engineering features. To make the system robust with respect to variations in sources of transverse illumination as well as rotation and leaf orientation of the image was achieved using data augmentation which might often be the case with field applications. Experimental results clearly prove the efficacy of the CNN architecture in identifying plant diseases using leaf images. The high accuracy, precision, and recall further support the model's ability to learn discriminative features of color, texture, and pattern automatically, without explicit feature engineering. Automatic extraction of such complex features from raw image data is where CNN shines, instead of requiring intensive human effort in defining them. By learning hierarchical patterns at multiple levels of abstraction, the model can interpret subtle variations that are typical for a disease class. Further, in order to make the system more robust against real-world variations in lighting, leaf orientation, and environmental conditions, augmentation techniques were applied. These include random rotation, flipping, and contrast adjustment that simulate natural field conditions and enable the model to generalize better over different scenarios. Data augmentation enhances model robustness against all these variations but also plays a significant role in model regularization by exposing the model to a variety of training samples. As a result, the model showed a better generalization for all variations in light, orientations, and image quality-something very common in practical agricultural environments. This ensures that the system stays reliable when it is run on mobile or edge devices for real-time disease detection. Finally, deep CNNs, supported by such techniques, represent an efficient and scalable solution for plant disease detection to reduce crop losses and support further development of agriculture.

Output Screenshots

Screenshot 1. SmartAgriDoctor system interface



Screenshot 2. Application feature dashboard.



Screenshot 3. Store interface for crop disease treatment purchase.

Screenshot 4. Market price analysis module for crops.

7. CONCLUSION AND FUTURE WORK

The suggested SmartAgriDoctor model presents the power of Convolutional Neural Networks CNNs to perform automated detecting of plant and crop diseases using the help of New Plant Disease Dataset offered by Kaggle. These combined methods of either systematized preprocessing, CNN feature extraction and fine-tuning training strategies resulted into a high-performance model in all assessment measures, corresponding to the parameters of accuracy, precision, recall and F1-scores higher than 97 percent. The results have established the reliability and scalability of deep learning in precision agriculture that in turn can provide farmers and stakeholders with an effective tool to conduct disease diagnosis in real-time and reduce crop losses, and improve food security. The little weight design also means that it can be implemented on mobile or at the edge devices and thus enables the system to be made available in the rural environment where resources are low. More so, augmentation of the dataset with more crops, variety of environmental conditions and early infection images will also see a continuous rise in robustness. The inclusion of explainable AI modules will also make it transparent with highlighting the affected area in the leaves which shall lead in to more confidence in the end-users.

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