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Crop Disease Detection Using Deep Learning Models

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Abstract:- Detecting plant diseases during the growth of plants is a critical challenge in agriculture, as late detection can lead to reduced crop yields and lower profits for farmers. To tackle this issue, researchers have developed advanced frameworks based on Neural Networks[1]. However, many of these methods suffer from limited prediction accuracy or require a vast number of input variables. This project comprises of CNN and LSTM models, the CNN component of the project has demonstrated remarkable accuracy, achieving a 98.4% success rate in identifying plant diseases from static images.

Keywords:- *CNN Architecture, VGG Architecture, Fully Connected Layers, VGG-19, Neural Networks, CNN, LSTM, Convolutional Layers.*

I. INTRODUCTION

Agriculture forms the foundational pillar of the Indian economy. Agriculture accounts for 10% of total GDP, with India accounting for 16%. In India, the agricultural sector either directly or indirectly supports nearly 70% of the population [2]. Therefore, the production of high-quality, disease-free crops are crucial for the development of the nation's economy. Similar to humans, different ripening stages or growth stages of plants are identified to different diseases. As a result, the overall production of crops and consequently the farmer's net profit are negatively impacted. The initial diagnosis of plant viruses is required to address this problem. Plant disease is manually detected by either farmers or agricultural scientists. But doing this requires a lot of effort and time.

These cutting-edge systems employ a wide range of training variables. As a result, the training and prognostication times of these processes are extremely long, or they necessitate the use of a machine with greater computational power. Figure-1 shows the images of various plant leaf diseases. This research proposes a novel crop disease detection system that leverages the power of deep learning, combining CNNs for image analysis and LSTM networks for sequential data processing. The integration of CNNs and LSTMs allows us to take advantage of their respective strengths to create a more robust and accurate detection model. This, in turn, substantially reduces the number of input variables, resulting in a reduction in training and detection accuracy.

The neuron architecture in the human brain serves as inspiration for deep learning techniques. These methods use Artificial Neural Network and their discrepancies, i.e., Convolutional neural network and Recurrent Neural Networks, to find hidden frameworks in the data. Compared to machine learning techniques, deep-learning methods have two major advantages [3]. To begin with, they do so automatically, doing away with the requirement for a completely separate feature extraction module. Second, processing large datasets with numerous dimensions takes less time when using Deep Learning techniques. Deep Learning methods are consequently suggested. Due to their efficiency with image data, DL techniques like CNN and LSTM are frequently used in applications involving computer vision.

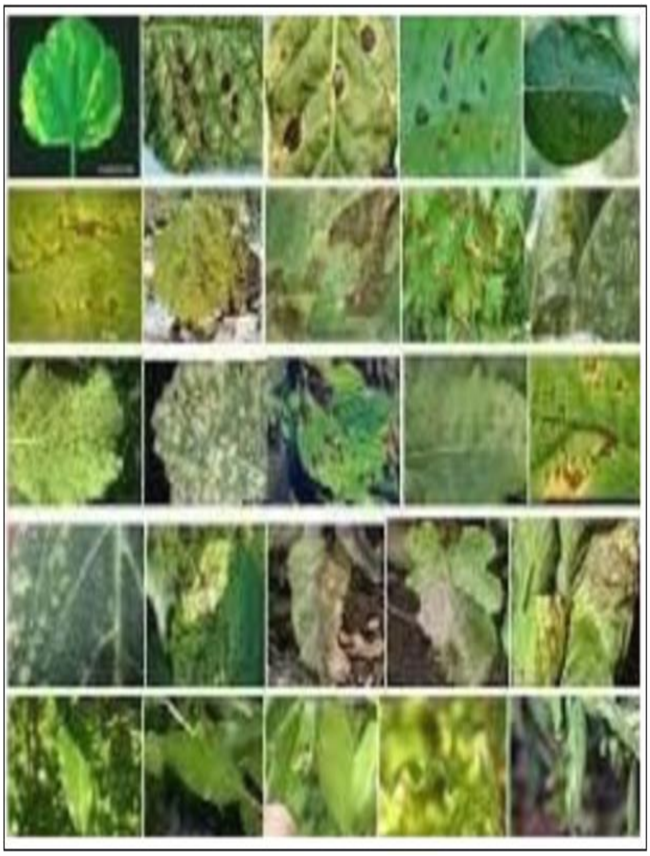

Fig 1 Various Types of Plant Leaf Diseases

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II. LITERATURE REVIEW

- *Survey on Crop Pest Detection using Deep Learning and Machine Learning Approaches [4]*

In this research paper by M. Chithambarathanu and M. K. Jeyakumar, The authors explore several methods for applying deep learning and machine learning techniques to identify plant diseases and crop pests. This paper includes the analysis of various existing methods such as DT (Decision Tree), SVM(Support Vector Machine), NB(Naïve Bayes). These techniques are based on machine learning. The authors also discover that models based on deep learning perform better than those based on conventional machine learning methods.

The authors point out that there is still space for improvement in the forecast accuracy of present methods, which led to the creation of a deep learning/machine learning hybrid approach. Better categorization outcomes and enhanced illness prediction performance are the goals of this suggested methodology. For even greater improvement, the article also recommends integrating metaheuristic techniques. Additionally, the study predicts the integration of mobile terminal processors and other Internet-based technologies in the future to allow real-time monitoring and pest identification in grain storage warehouses, such as the Agricultural Internet of Things (IoT). This connection is considered a first step towards modernising and intelligently transforming agriculture.

- *Machine Learning for Detection and Prediction of Crop Diseases and Pests: A Comprehensive Survey [5]*

The research paper authored by Tiago Domingues, Tomás Brandão, and João C. Ferreira provides a comprehensive survey for the administration machine learning (ML) approaches as the observation and prognostic of crop infection and pests. It highlights the importance of long-term datasets encompass weather, diseases, and pests' data for accurate forecasting using time-series ML models like Recurrent Neural Networks (RNN) and the relevance of NDVI measurements for crop development insights.

Additionally, the paper talk about the effectiveness of deep learning and Convolutional Neural Network (CNN) models in the observation and categorization of diseases and pests in crop images, emphasizing the challenges associated with data scarcity in real-life conditions. The study also underscores the need for further research to explore the combination of different data modalities in pest and disease forecasting. In summary, the paper serves as a valuable overview of ML appeal in crop disease and pest management, highlighting the potential of various ML techniques while identifying areas for future research and development in this field.

- *Deep CNN Models in Plant Disease Identification [6]*

The research paper discusses the application of deep learning models, particularly Convolutional Neural Networks (CNNs), for the identification of plant diseases. The reseach paper is proposed by Harjeet Kauri, Deepak Prashar and Vipul Kumar Various. Well-known CNN architectures such as AlexNet, GoogLeNet, Inception, and ResNet are explored in the context of plant disease detection. The study highlights that deep learning approaches have become increasingly popular in recent years, but identifies certain research gaps. Most existing work primarily relies on datasets from PlantVillage, which predominantly contain images from controlled laboratory environments with simple backgrounds. The paper suggests the need for incorporating images from field environments and emphasizes the importance of adapting deep learning models to account for changes in the severity of plant diseases over the entire life cycle of plants.

- *Crop Leaf Disease Detection and Classification using Machine Learning and Deep Learning Algorithms by Visual Symptoms [7]*

The research paper reviews the use of machine learning and deep learning algorithms for crop leaf disease detection and classification based on visual symptoms. It highlights that deep learning techniques outperform machine learning techniques in accuracy, especially when using modified CNNs, optimized deep learning models, and transfer learning. Notably, a multi-channel model achieved the highest accuracy of 99.5% in deep learning, while SVM with a linear kernel reached 99% in machine learning. The paper discusses the five key steps in developing a crop disease identification system: image acquisition, pre-processing, segmentation, feature extraction, and classification. It emphasizes the need for more research and datasets to enhance disease detection in large-scale crops, underlining the importance of integrating computer vision and machine learning into agricultural automation technologies such as UAVs and smartphones.

- *An Advanced Deep Learning Models-based Plant Disease Detection [8]*

The research paper provides a comprehensive review of recent advancements in using Machine Learning (ML) and Deep Learning (DL) techniques for plant disease detection. It highlights the significance of gathering diverse images from different plant growth stages, seasons, and regions to enhance the model's robustness and generalization. The paper emphasizes the importance of incorporating meteorological and plant health data for efficient disease identification and prevention. It also suggests the use of unsupervised learning and knowledge from human visual cognition to improve DL model training. The study acknowledges the challenges, such as data availability and distinguishing healthy plants from diseased ones, while showcasing the substantial improvements in plant disease identification achieved through DL and ML methods. Overall, this research contributes valuable insights to both researchers and industry professionals in advancing plant disease detection and prevention.

- *Plant Disease Prediction using Hybrid Model [9]*

The research paper discusses the effectiveness of a hybrid model for plant disease prediction, which combines machine learning, deep learning, and image processing techniques to accurately identify diseases in plants like pepper, tomato, and potato. The hybrid model's ability to capture complex relationships between plant features and symptoms leads to precise disease diagnosis, and its real-time predictions can help farmers take timely preventive measures, improving agricultural practices and crop yields. The study highlights the potential benefits of the CNN-LSTM model for plant disease prediction, emphasizing that its performance depends on factors like training data quality and model architecture, with a reported best accuracy of 0.9325. Overall, this research offers a promising solution to enhance food security and agricultural productivity by effectively managing and preventing plant diseases.

- *Plant Disease Detection using CNN" [10]*

The research paper by Nishant Shelar, Suraj Shinde, Shubham Sawant, Shreyash Dhumal, and Kausar Fakir presents a deep learning model for plant disease detection using Convolutional Neural Networks (CNNs). They achieved an impressive accuracy rate of 95.6% by employing early stopping during training over 50 epochs. The paper demonstrates the successful classification of 38 different plant diseases across 13 plant species, including tomato, strawberry, soybean, raspberry, potato, corn, and others. The authors also visualized the training and validation accuracy and showcased the model's capability to distinguish between healthy and diseased plant leaves for various plant species. The research showcases the effectiveness of their approach, including the use of the VGG-19 model and the deployment of the model on an Android app, with ongoing efforts to further improve accuracy in both the app and the model.

- *Systematic Study on Deep Learning-based Plant Diseasedetection or Classification" [11]*

The research paper by Sunil, Jaidhar, and Patil addresses the critical issue of plant disease detection, emphasizing the economic impact of such diseases on agricultural production. Traditional methods relying on domain experts are limited by their availability, travel costs, and consultation fees. To overcome these challenges, the paper conducts a systematic study that reviews 160 research works related to plant disease detection, focusing on Deep Learning-based and Machine Learning-based approaches. The study categorizes these approaches into single network models, hybrid models, and real-time detection methods, covering 50 different plant leaf disease datasets. Additionally, the research highlights the significance of hyperparameters in deep learning and identifies key challenges and research gaps in the field of plant disease detection, underscoring the need for cost-effective and robust automated solutions.

- *A Review of Plant Disease Detection and Classification Methods" [12]*

This research paper provides an extensive review of recent advances in the domain of crop leaf disease detection and classification using image processing, machine learning, and deep learning techniques. The authors highlight the significance of accurate disease detection for improving agricultural yields sustainably. The paper surveys various methodologies, focusing on dataset characteristics, the number of images and classes, algorithms employed, and the performance of convolutional neural network (CNN) models. Additionally, it offers insights into the suitability of these algorithms for deployment in different settings such as standard systems, mobile/embedded devices, drones, robots, and unmanned aerial vehicles. The paper also discusses performance metrics, identifies limitations, and suggests areas for future research to enhance real-time automated crop leaf disease detection systems.

- *Plant Disease Detection using Image Processing and Machine Learning Algorithm [13]*

The research paper presents a novel approach for plant disease detection using image processing and machine learning techniques. The study utilizes MATLAB to process and segment diseased leaf images into clusters based on their diseases. It calculates the functionality of co-occurrence after thresholding the RGB components of the images and employs K-Means clustering for classification. The system relies on image processing, K-Means, and neural networks to predict diseases in 25 leaves belonging to 5 different categories. The results demonstrate an overall accuracy of approximately 89.8% for pomegranate leaf disease detection and 91% for potato leaf disease detection, showcasing the effectiveness of the proposed hybrid algorithms and segmentation techniques.

In conclusion, the research introduces a robust approach for automatic disease segmentation and classification, leveraging K-Means clustering and neural networks.

III. LITERATURE SURVEY OF THE PAPERS

Table 1 Literature Survey of the Papers

Year and Citation	Article/ Author	Technique	Dataset Source	Evaluation Parameter
2023	M. Chithambarathanu and M. K. Jeyakumar	Random Forest, SVM, Decision Tree, CNN.	Google Scholar	Accuracy using CNN 94.96% Accuracy using DCNN 95.28% Accuracy using SVM 92.65%
2023	Tiago Dominguez, Tomas Brando, and Joao C. Ferreira	SVM, Random Forest, VGG-16.	Google Scholar	F1-Score (0.93), Accuracy using SVM 94.6% Accuracy using RF 95.5% Accuracy using VGG-16 98%
2023	Harjeet Kauri, Deepak Prashar and Vipul Kumar	CNN, Random Forest,	Data Mendeley	Accuracy using CNN 92.8% Accuracy using RF 94.56%

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		RestNet		Accuracy using ResNet 97.28%
2023	**Pallepati Vasavi, Arumugam Punitha and Venkat Narayana Rao[7]**	**SVM, KNN**	**Digitial cameras, drones, UAV**	**Accuracy using KNN 99%, Accuracy using SVM 99.5%**
2023	Muhammad Shoaib, Babar Shah, Shanker al Sapagh, Akhtar Ali, And Asad Ullah	CNN, SVM	Complied dataset from Google Scholar, Kaggle	Accuracy using CNN 98% Accuracy using SVM 94%
2023	Mr. Gopinath V, Ilakiya V, Nandhini R, Monikasri B, Shalene V	CNN and LSTM	Kaggle , Mendeley Data	Accuracy 93.2%
2022	Nishant Shelar, Suraj Shinde, Shubham Sawant and Shreyansh Dheyal	CNN	Data Mendeley	Accuracy 95.6%
2023	C.K. Sunil, C.D. Jailandar And Nagamma Patil	R-CNN, Inception V3	Own Dataset	Accuracy using R-CNN 99.7% Accuracy using Inception v3 99.4%
2023	Nauman Qadaeer, Thabit Sabbah and Muhammad attique khan	CNN	Wheat Fields From Kotli Kashmir	Val Accuracy 93% Precison-0.94 F1-Score-0.93,Recall-0.93
2022	S. Nandhini and K. Ashokkumar	AlexNet, GoogleNet,	Data Mendley, Kaggle	Accuracy 99.35%

IV. CONCLUSION FROM REVIEWING THE PAPERS

The key accuracy result among these Research Papers is that Support Vector Machine (SVM) and KNN 99% and 99.5% respectively [7]. This accuracy level is exceptionally high and indicates that the model was highly effective in correctly identifying and classifying different plant diseases within the dataset. The only drawback that occurred while researching into that paper is that its dataset.

The primary constraints often encountered in crop disease detection systems relying on visual symptom analysis include a notable deficiency of extensive and publicly accessible datasets. While Plant Village stands as a valuable resource, it remains the solitary widely available dataset generated within controlled environments. Some researchers have crafted their proprietary datasets; however, they are typically unwilling to share access with the broader community for comparative analysis. Moreover, it's important to note that the Plant Village dataset may not encompass imagery of commercial crops such as chili, which exhibit a diverse array of diseases.

The accuracy level achieved in this research is exceptionally high as the dataset available on the web has not more than 50k images, plus the model is no longer focusing on the sequential learning of the crop disease detection. So the top most priority is to build and implement a model which can give high accuracy in predicting the crop's disease as well as the disease's progression analysis.

Although in the market various projects have been built with the motive to achieve high accuracy in the crop disease detection but they have been trained on the small size dataset due to the availability and the quality of the dataset. The dataset which we have complied compresses of 68.9k images that are labelled with the disease name and also categorised with two parameters i.e. Healthy and Unhealthy. Moreover the model which we have built is using latest pre-trained model VGG-19 whose expertise includes image classification and feature extraction. Growth of pre-trained models are given below.

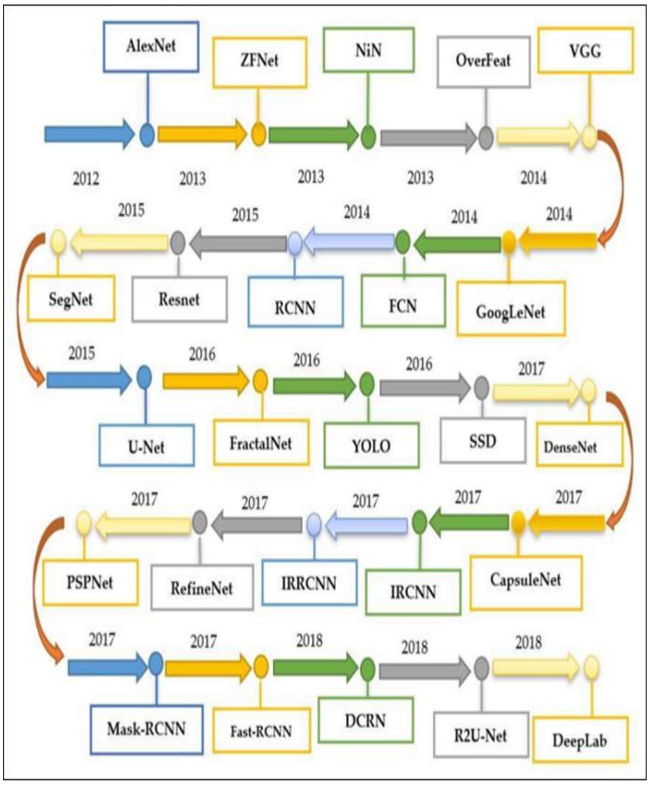

Fig 2 Summary of the Evolution of Various Deep Learning Models from 2012 Until Now

V. DOMAIN KNOWLEDGE

A. *Overview of Proposed System*

➤ *Problem Definition:*

The proposed project aims to develop a Crop Disease Detection System by using CNN networks for image classification and feature extraction and LSTM networks for disease progression analysis. This system will integrate advanced dl techniques which are used to foresee and classify the crop disease based on the symptoms captured through images from the available dataset. Using CNNs to extract relevant information from pictures and the ability of LSTMs to simulate temporal relationships in the course of disease, the system will provide farmers with timely and precise recommendations for disease management, ultimately enhancing crop yield and food security

➢ *Problem Architecture:*

The Proposed system comprises of using some basic deep learning algorithm like CNN and LSTM. Although for the implementation of the crop disease detection system we have chosen the pre trained model VGG-19. Moreover the VGG-19 is the latest model available on the web, its compatibility for the image's feature extraction is strong.

Hence the proposed system will use VGG-19 for the classification or categorizing them into the Healthy and Diseased plant crop. The system will analyze linguistic cues and extrinsic information to determine the plant's disease. This project can help in early detection and management of crop diseases, which is crucial for agriculture.

➢ *The Proposed System will Include these Steps:*

- *Data collection:*

✓ Accumulate a comprehensive dataset with images containing healthy and diseased plant crops. Ensure that the dataset is well-labeled with information about the type of disease and the plant crop's name.
✓ Preprocessing of the images i.e. resizing them to a particular uniform size and normalizing the pixel values. Augmenting the dataset if needed (e.g., rotation, flipping, brightness adjustments).
✓ Resizing the images to a consistent size (e.g., 224x224) for compatibility with VGG19.

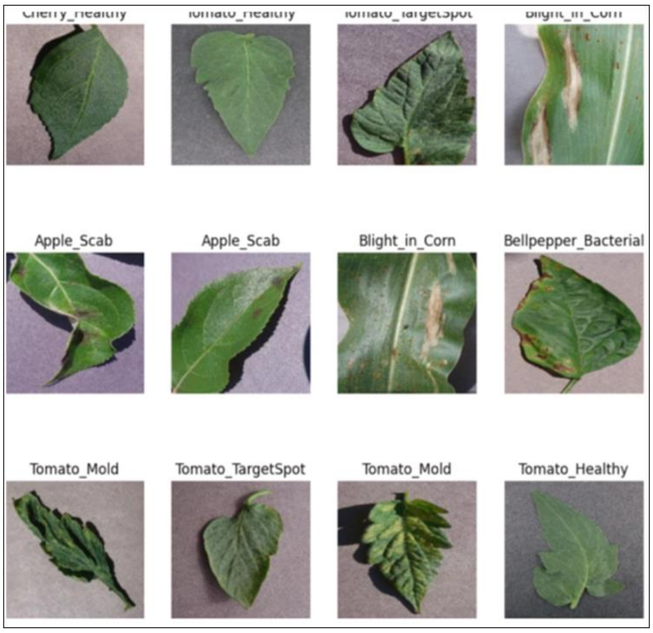

Fig 3 Samples Images from the Dataset which are Preprocessed

- *Model Selection:*

✓ CNNs are the most popular choice for image classification tasks, so a CNN-based model is a good starting point. Some popular CNN architectures include VGG19, ResNet, and MobileNet.
✓ Further the selection of deep learning model is the main task for the image classification. Here we are using VGG-19 for the implementation of the model.
✓ LSTM networks can also be used for plant disease detection, especially for tasks such as disease progression analysis.

- *Data Splitting:*

Splitting the dataset and categorizing it into training, validation and testing sets has already been done and uploaded on the Kaggle Datasets.

- *Transfer Learning:*

Once a pre trained model is selected, it needs to be applied on the preprocessed dataset. This involves feeding the images to the model and allowing it to learn the features that are associated with different crop diseases. The model will then be able to use these obtained features from the images to classify the new images into category like healthy or diseased.

- *Image's Feature Extraction using Convolutional Neural Network(CNN):*

Executing the CNN model in order to enable it to extract features from the input photos. Several layers are built into the CNN's architecture, including:

✓ Multiple Convolutional layers
✓ Pooling Layers
✓ Fully Connected Layers

- *LSTM for Sequence Learning:*

✓ Convert the feature vectors extracted by the CNN into sequences.
✓ Implement the LSTM network to learn the temporal dependencies in the feature sequences. This is useful for capturing how diseases evolve over time.

- *Training the Model:*

✓ Train the model (CNN & LSTM) on the training dataset. Use an appropriate loss function for classification, such as categorical cross-entropy.
✓ Monitor training with validation data to prevent overfitting. Apply techniques like dropout, batch normalization, and early stopping (if needed).

- *Evaluating the model:*

Analyze the model's performance with measures such as these on the testing dataset:

✓ Accuracy (Both Training and validation)
✓ Precision
✓ Recall

- *Hyperparameters Tunning:*

Fine-tune hyperparameters of both the CNN and LSTM models, such as:

- ✓ Batch Size
- ✓ Number of layers/units in LSTM

VI. METHODOLOGY

A. CNN (Convolutional Neural Network)-

An artificial neural network (ANN) with specific capabilities for processing and analysing visual information is called a convolutional neural network (CNN). Tasks requiring object identification, categorization, and picture recognition are especially well-suited for them. CNNs excel at capturing the spatial relationships between pixels in an image, allowing them to learn and identify intricate patterns that are often difficult or impossible to detect with traditional methods.

Convolutional layers play a crucial role in Convolutional Neural Networks (CNNs). They operate by utilizing a collection of filters to process the input image. These filters, which are applied to different areas of the picture, are tiny weight matrices. Convolutional layer output is a collection of feature maps, or more specifically, a collection of pictures that highlight various aspects of the input image.

By lowering the spatial resolution of these feature maps, pooling layers help to lower the network's computational cost and lessen the chance of overfitting. Fully connected layers, in essence, resemble the layers commonly found in traditional neural networks. They take the output of the pooling layers and connect them to a layer of neurons that produces the final output of the network.

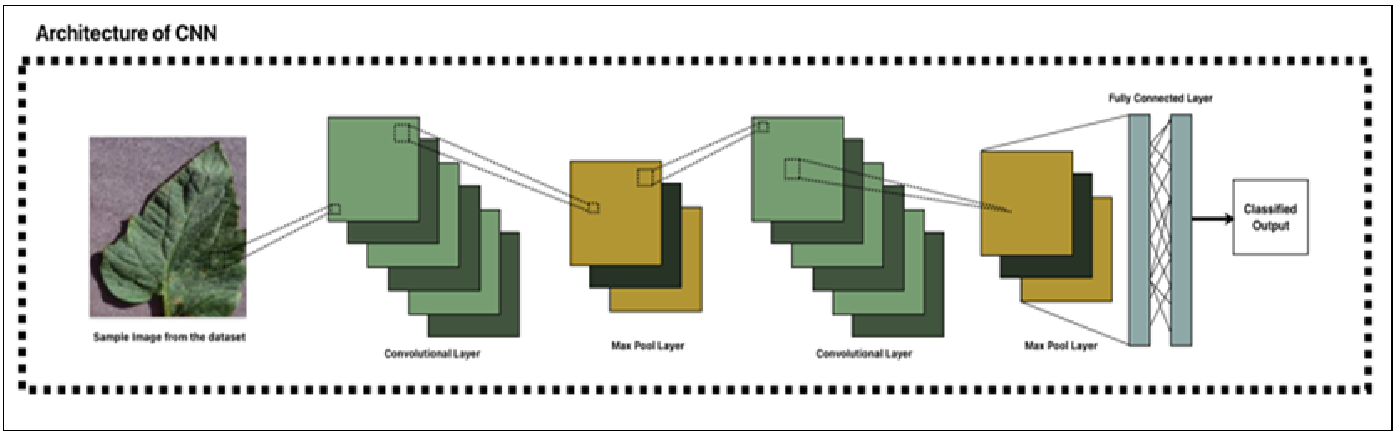

Fig 4 Basic Architecture of CNN Model based on Plant Leaf.

Convolutional Neural Networks (CNNs) undergo supervised learning, wherein a dataset of labelled images is provided to the network. Through this process, the network gains the ability to associate image features with their corresponding labels. Once trained, the network uses its learned features to predict new image classifications.

In several image-related tasks such as object recognition, semantic segmentation, and image classification, CNNs have continuously shown outstanding performance. They find applications beyond image tasks, extending to domains like natural language processing, machine translation, and video analysis.

The suitability of CNNs for plant disease detection is attributed to their capacity to discern spatial features within images. The identification of spatial features is crucial in plant disease detection, as they enable the recognition of patterns within the distribution of affected plant tissue.

For instance, a CNN can be trained to recognize distinct patterns like the circular lesions characteristic of fungal leaf spot diseases. Additionally, the network can learn to distinguish the irregular shape and texture associated with bacterial leaf blight diseases. CNNs are also able to learn temporal features from sequences of images. This is useful for tasks such as disease progression analysis. For example, a CNN can be used to track the changes in the size and shape of a diseased leaf over time.

- ➢ *CNNs are Typically used for Plant Disease Detection in these ways:*

- Using photos of plant illnesses identified with the associated plant disease to train the CNN model. CNN gains the ability to identify various plant diseases by identifying spatial and temporal features in the images.
- Once the model is trained on the CNN, it is ready to classify the diseases in the crops.
- The CNN gives the probability score for every crop disease as an output, and the class that gets the highest probability score will get predicted and marked as the correct class.

B. VGG-19-

VGG19 is a CNN architecture initially crafted by researchers from the University of Oxford, renowned for its robust performance in image classification tasks. While it offers impressive results, it demands significant computational resources for training. Nonetheless, a multitude of pre-trained VGG19 models are accessible online, making it an ideal candidate for transfer learning. In utilizing VGG19 for plant disease detection, the primary step entails removing the pre-trained model's classifier layer. Subsequently, a novel classifier layer is appended, equipped with the required number of classes (e.g., healthy and diseased). This adapted model is then fine-tuned using a plant disease dataset. Once training is complete, the model becomes proficient at categorizing new plant images as either healthy or diseased. Each class receives a probability score; the projected label belongs to the class with the highest score.

It belongs to the VGG model family, celebrated for their straightforward yet effective approach to image classification. With 19 layers total—16 convolutional layers and 3 fully linked layers—VGG19 in particular stands out for its depth. K Simonyan and A. Zisserman's Publication, "Very Deep Convolutional Networks for Large-Scale Image Recognition," introduced the concept. In the year 2014.

➢ *Here's a Detailed Overview of the Architecture of VGG19:*

➢ *Input Layer:*

An RGB picture with a fixed size of 224 by 224 pixels is inputted into VGG19. Red, Green, and Blue are the three colour channels of the input picture.

➢ *Convolutional Layers (Blocks):*

VGG19 is composed of five series of convolutional blocks, each of which is accompanied by a subsequent max-pooling layer. Multiple convolutional layers precede Rectified Linear Unit (ReLU) activation functions inside each block. The quantity of filters progressively grows as you delve deeper into the network.

- *Block 1:*

✓ Two 2D convolutional layers with "same" padding and 64 filters of 3x3.
✓ An additional layer called max-pooling with a 2x2 window and a 2x2 stride comes next..

- *Block 2:*

Two 3x3 2D convolutional layers with 128 filters per and "same" padding make up this block. The max-pooling layer that follows has a 2x2 window and a 2x2 stride. Two 3x3 2D convolutional layers with 128 filters per and "same" padding make up this block. The layer beyond that is a max-pooling layer with a window and stride of two by two dimensions.

- *Block 3:*

In this block, there are four 2D convolutional layers, each with 256 filters of size 3x3, employing 'same' padding. Subsequently, a max-pooling layer with a 2x2 window and a stride of 2x2 is applied.

- *Block 4:*

This block consists of four 2D convolutional layers, each employing 512 filters of size 3x3 and 'same' padding. After the convolutional layers, there is a max-pooling layer with a 2x2 window and a stride of 2x2.

- *Block 5:*

In this block, there are four 2D convolutional layers with 512 filters of size 3x3, utilizing 'same' padding. Following these convolutional layers, a max-pooling layer is applied with a 2x2 window and a stride of 2x2**.**

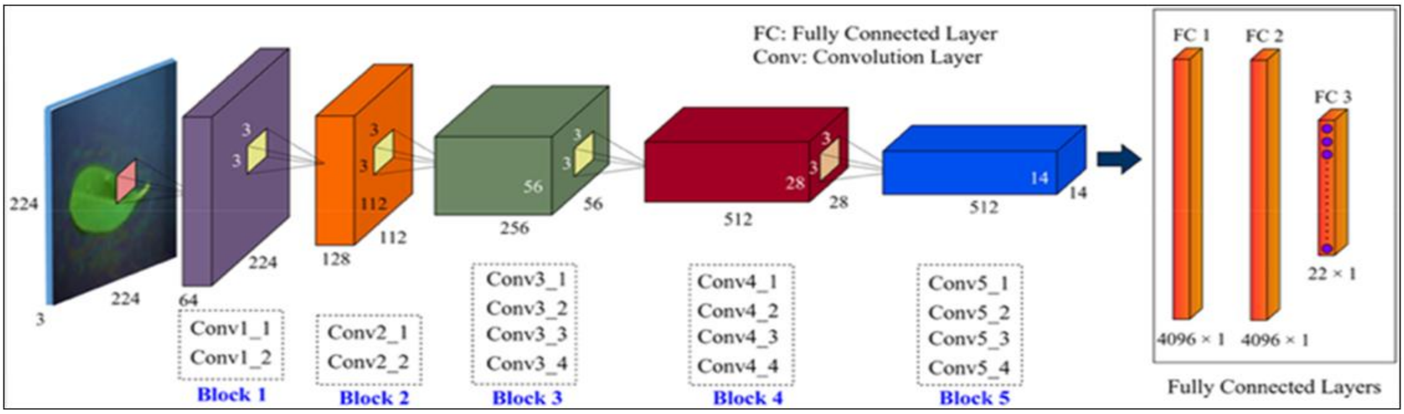

Fig 4 VGG-19 Architecture

➢ *Fully Connected Layers:*

- VGG19's architecture includes three fully connected layers following the convolutional blocks.
- The first fully connected layer comprises 4096 neurons with a ReLU activation function.
- The second fully connected layer also consists of 4096 neurons with a ReLU activation function.
- The third fully connected layer serves as the output layer and features 1000 neurons, representing the 1000 classes present in the ImageNet dataset, which was the dataset initially used to train VGG19..
- It typically uses a softmax activation function to produce class probabilities.

➢ *Output:*

The VGG19 network produces a probability distribution across 1000 classes, rendering it well-suited for image classification tasks. VGG19 is renowned for its consistent architectural design, featuring a repeated arrangement of convolutional and max-pooling layers.

This uniform and deep structure enabled it to achieve cutting-edge performance in image classification tasks when it was originally introduced.

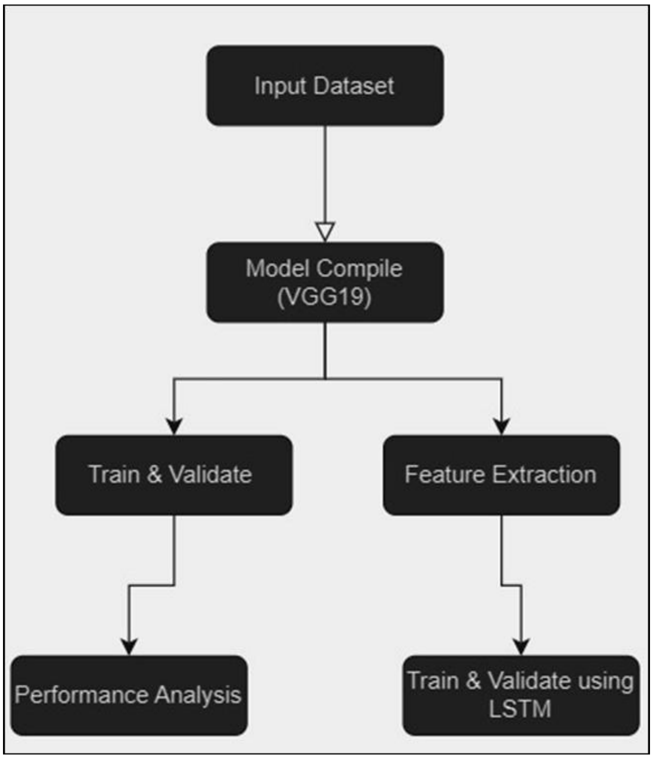

Fig 5 Model Overview for the Proposed System

C. Long Short Term Memory (LSTM)-

Plant disease identification is a perfect application for LSTM networks, a subtype of recurrent neural networks (RNNs), because of its capacity to identify temporal relationships in sequential data. This is important for plant disease detection because it allows the network to identify patterns in the distribution of disease symptoms over time.

For example, an LSTM network can be used to track the changes in the size and shape of a diseased leaf over time. This information can then be used to classify the plant disease or to predict the progression of the disease.

➢ *LSTM Networks can be used in Crop Disease Detection Systems in the following ways:*

- *Classifying the Diseases:*

LSTM networks can be used to classify plant diseases by analysing sequences of plant images. For example, A collection of crop photos annotated with the corresponding crop disease might be used to train an LSTM network. An example of a temporal characteristic that the LSTM network would be trained to extract from the photos would be the variations in the size and form of illness symptoms over time. The network could then use these features to classify new plant images as healthy or diseased.

- *Disease Progression Analysis:*

LSTM networks can also be used to predict the progression of plant diseases. This can be done by training an LSTM network on a dataset of plant images that are labelled with the corresponding plant disease and the stage of the disease. The LSTM network would acquire the ability to identify temporal characteristics in the pictures that correspond to the illness's progression. The network could then be used to predict the stage of the disease for new plant images.

VII. FUTURE SCOPE OF THE PROJECT

- Deploy the trained model to a server or cloud service, where it can be accessed by users for real-time or batch processing of images.
- Create a user-friendly interface for users to upload images and receive disease detection results.
- Remote Sensing and Drones, Integration with remote sensing technologies and drones can enable large-scale, automated monitoring of agricultural fields. Drones with cameras are able to take pictures, which the CNN-LSTM model processes to identify illnesses.
- The project's future scope may involve fine-tuning the LSTM model to improve its accuracy and consistency. Continued research in LSTM architecture, hyperparameter tuning, and larger training datasets can contribute to enhanced performance.

VIII. CONCLUSION

In conclusion, A major advancement in contemporary agriculture and crop management is the creation of a crop disease detection system employing Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks.. This project offers a promising solution to the pressing issue of early disease detection and monitoring in plants, with far-reaching implications for crop yields, sustainable farming practices, and food security.

The project that we had built comprises of CNN and LSTM models, the CNN component of the project has demonstrated remarkable accuracy, achieving a 98.4% success rate in identifying plant diseases from static images. This level of accuracy is a testament to the effectiveness of deep learning in image classification tasks.

Although the LSTM model has achieved a comparatively lower accuracy of 70%, its role in analyzing sequential data, such as disease progression, is crucial. The LSTM provides valuable insights into the temporal aspect of disease development, enhancing the overall system's ability to understand disease dynamics.

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