"SMART FARMING: DEEP LEARNING FOR DISEASE DETECTION IN CROP"

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ABSTRACT:
Crop diseases present a major obstacle to agricultural output, food safety, and economic viability globally. Timely and precise identification of crop diseases is essential to reduce losses, uphold crop health, and guarantee maximum yields. This study investigates the use of Convolutional Neural Networks (CNNs) for the automatic identification and categorization of crop diseases through images. CNNs, recognized for their outstanding effectiveness in image recognition tasks, are utilized to examine visual patterns and signs of diseases on crop foliage. The research utilizes advanced CNN architectures, such as VGG16, ResNet, Inception, and DenseNet, to create a strong detection framework. DenseNet, in specific, shows predominant classification precision, highlighting its potential as an successful arrangement for malady conclusion. A comprehensive dataset comprising pictures of solid and infected crops is utilized to prepare and assess the models. Preparatory comes about show that CNN-based models accomplish tall precision and outflank conventional manual review strategies in terms of speed and unwavering quality The proposed framework gives an important instrument for ranchers and rural partners, empowering convenient distinguishing proof of edit infections and encouraging the execution of focused on mediations.

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***Composite indicators**: Deep learning (DL), Convolutional neural network (CNN), machine learning (ML), Artificial intelligence (AI), feature extraction (FE), Image processing, VGG 16, Crop disease recognition, Dense Net.*

1. INTRODUCTION

I. Background

Agribusiness is the spine of the worldwide economy, giving nourishment, crude materials, and work to a critical parcel of the populace. In any case, agrarian efficiency faces various challenges, counting bug invasions, unusual climatic conditions, and most vitally, trim infections. Edit infections are caused by pathogens such as parasites, microscopic organisms, and infections, driving to diminished abdicate, financial misfortunes, and nourishment frailty. Concurring to considers, plant infections are mindful for a significant rate of trim misfortunes every year, undermining the business of ranchers and the worldwide nourishment supply chain. Crop diseases have long been recognized as a significant threat to food security, with the challenges posed by climate change and the need for effective disease management being closely linked to the principles of sustainable agriculture. These issues considerably diminish crop yields and adversely affect their quality. As modern technologies strive to ensure food security for a global population nearing 8 billion, the scarcity of local expertise to promptly address the emergence of plant diseases remains a critical challenge for agricultural producers, particularly smallholder farmers. These farmers, who contribute over 80% of the world's agricultural output, reportedly suffer yield losses exceeding 50% due to various diseases.

Historically, the detection of Crop diseases has relied on human observation. To minimize unnecessary expenditure of financial and human resources and to promote healthier agricultural practices, agronomists would greatly benefit from the creation of an automated computer system designed for the identification and classification of plant diseases. Artificial intelligence (AI) encompasses a domain known as computer vision, which empowers computers and systems to derive valuable insights from digital images, videos, and other visual data, enabling them to respond or provide recommendations based on that information. Computer vision allows machines to perceive, observe, and understand, paralleling how artificial intelligence equips computers with cognitive capabilities.

The automation of localization and classification of crop diseases presents considerable challenges, primarily due to the substantial variations in leaf size, shape, colour, and orientation. This research tackles these issues by introducing a tailored Convolutional Neural Network (CNN) framework utilizing ResNet-50. To effectively address this problem, it is essential to employ machine learning (ML) and deep learning (DL) algorithms for the early prediction of crop diseases. Traditional algorithms, such as Random Forest, Support Vector Machines (SVM), and Convolutional Neural Networks like ResNet-9 and ResNet-50, are commonly used. CNNs function as neural networks designed for various applications, particularly in image processing, classification, segmentation, and other related fields.[1]

In this study, two advanced CNN architectures, VGG16 and InceptionV3, were evaluated under different conditions. Techniques such as fine-tuning, transfer learning, and training from the ground up were employed to measure their effectiveness. The results indicated that fine-tuning the model during training yielded the highest performance for both architectures. While these deep learning models demonstrate strong practical performance, a significant drawback is their extensive number of parameters, a challenge that aligns with findings from earlier research.[2]

II. The Significance of Technology in Detecting Diseases

Technologyhas greatly changed agricultural methods, with one of its most influential uses being in the identification and handling of crop diseases. The emergence of precision agriculture has established technology as a fundamental component of contemporary farming methodologies. Automated and intelligent systems possess the capability to revolutionize agriculture by equipping farmers with precise and timely data. Among these technological innovations, the use of artificial intelligence (AI) for image-based disease detection has attracted significant interest. In particular, Convolutional Neural Networks (CNNs), which are a category of deep learning, have demonstrated substantial potential in the realm of image recognition and classification. CNNs are capable of autonomously extracting and learning features from images, rendering them exceptionally effective for the analysis of visual data, such as images of crop foliage. By utilizing CNNs, it becomes feasible to identify and categorize crop diseases with remarkable accuracy, thereby reducing reliance on manual inspections and facilitating early diagnosis.

The Convolutional Neural Network (CNN) consists of multiple convolutional and pooling layers, culminating in fully connected layers. One of the primary benefits of CNNs is their ability to automatically extract features from input images. The architecture of a CNN is primarily made up of three key components: the convolutional layer, the pooling or subsampling layer, and the fully connected layer.

III. Datasets.

Our model's dataset is sourced from the openly accessible Kaggle platform for plant illness identification. This dataset encompasses a variety of images showcasing distinct plants, totaling 5465 images spread across 15 categories, which include both healthy and infected foliage. Each image has a resolution of 256x256x3. Prior to integrating the images into the model, the researcher carried out an initial data exploration. In the realm of statistics, exploratory data analysis (EDA) is a technique used to inspect and summarize key features of data sets, frequently using visual methods. The visualization of the data revealed a significant issue with class imbalance in the training dataset. Consequently, the researcher implemented an up-sampling method to address this problem. To ensure all classes had an equal number of images, the researcher duplicated images from underrepresented classes, applied augmentation techniques to them, and then incorporated these augmented images into the dataset. This process was repeated until the number of images in each class was balanced.

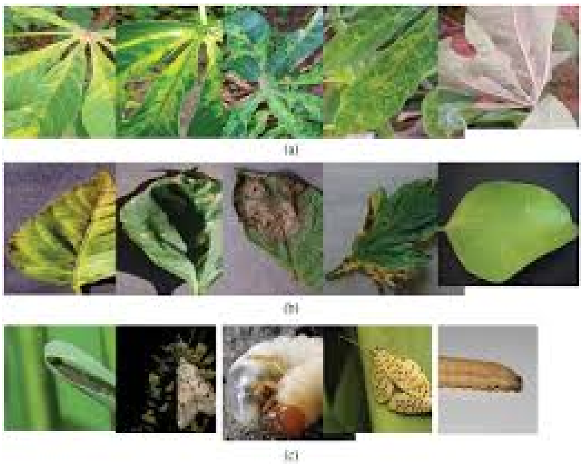

Fig. 1, 2 sample Dataset

2.LITERATURE SURVEY

The method of detecting crop illnesses has sparked conversation over time. Numerous scientists have cra fted various effective models for diagnosing plant ail ments through machine learning methods.

Kumar et al. (2020) introduced a CNN-based model specifically designed for the detection of tomato leaf diseases. This model achieved an impressive 95.6% accuracy in classifying five distinct diseases as well as healthy leaves. However, the study faced challenges due to limited diversity in the dataset, which restricted the model's generalizability. Moreover, performance fluctuations were observed under varying lighting conditions, emphasizing the need for a more robust dataset and preprocessing techniques [3].

Building on the concept of transfer learning, Singh et al. (2021) evaluated pre-trained CNN models such as ResNet and VGG for crop disease detection. ResNet50 emerged as the most effective model, achieving an exceptional accuracy of 97% on a public dataset. Despite these remarkable results, the study highlighted the computational intensity of ResNet50, making its deployment in real-time scenarios challenging, particularly in resource-constrained environments [4].

Patel et al. (2019) focused on applying CNNs for the classification of maize plant diseases using locally collected datasets. Their model achieved 92% accuracy, demonstrating the potential of CNNs in disease classification. However, the research revealed that the model struggled to differentiate visually similar diseases, such as certain fungal infections, leading to occasional misclassifications. This limitation underscores the importance of feature engineering or the inclusion of advanced architectures for improved specificity [5].

Gupta et al. (2022) proposed an innovative approach by designing an improved CNN architecture integrated into a smartphone application for real-time crop disease detection. Their solution provided farmers with instant feedback, achieving an accuracy of 90% even under diverse environmental conditions. Despite its utility, the application experienced slower detection rates on low-resource devices such as entry-level smartphones, highlighting the need for further optimization in terms of model size and efficiency [6].

Sharma et al. (2023) explored a unique combination of visual and spectral data for early-stage disease detection in wheat crops. Their CNN-based model achieved a notable accuracy of 94.8%, proving effective in identifying diseases in their initial stages. However, the reliance on specialized equipment to capture spectral data added to the complexity and cost of the solution, posing challenges for large-scale or low-budget implementations [7].

Mohanty et al. (2016) developed a CNN-based framework that achieved 99.35% accuracy in identifying 38 plant disease classes across 14 crop species, though performance declined when tested on diverse environmental conditions, underscoring the need for more diverse datasets [8]. Similarly, Sladojevic et al. (2016) successfully classified 13 plant diseases with 96.3% accuracy but faced challenges when visual symptoms were indistinguishable from natural aging or environmental stress. Too et al. (2019) compared pre-trained CNN architectures like VGG16, ResNet, and DenseNet, with DenseNet achieving 99.75% accuracy due to its feature reuse mechanism, though its computational cost limited real-time applicability [9].

Ferentinos et al. (2018) achieved 99.53% accuracy in greenhouse environments using over 87,000 images, but their model’s effectiveness in real-world conditions was limited [10]. Picon et al. (2019) proposed a lightweight CNN model for grapevine disease detection, achieving over 90% accuracy with reduced computational requirements, making it suitable for mobile deployment, albeit specific to grapevines [11]. Brahimi et al. (2017) used transfer learning with AlexNet, achieving high accuracy on a small dataset but requiring extensive preprocessing for consistent results [12]. Saleem et al. (2021) demonstrated that CNNs could detect early-stage diseases with hyperspectral images, outperforming traditional methods but requiring specialized equipment [13].

Hybrid approaches, such as the CNN-RNN model proposed by Chen et al. (2020), improved accuracy in sequential data scenarios but increased model complexity [14], limiting real-time deployment. Zhang et al. (2022) integrated IoT and CNNs for real-time disease detection, achieving over 93% accuracy but faced challenges in ensuring data privacy and security during transmission [15]. Finally, Ashok et al. (2021) introduced explainable AI (XAI) techniques to enhance interpretability by highlighting critical image areas responsible for disease classification, though this added computational overhead [16].

In our research, we primarily employed the CNN architecture known as the DenseNet model as our pre-trained foundation for Transfer Learning. Several other notable pretrained frameworks (VGG16, Inception V3, and ResNet152V2) were also examined along with various Transfer Learning configurations, and these were compared to DenseNet. In addition, a creation was made to increase the precision of the detection.

3.PROPOSED METHODOLOGY

The suggested methodology describes a methodical way to create, train, and assess a CNN-based crop disease detection system. The following steps are part of it:

1.Problem Definition: Determine the extent of the issue, with a particular emphasis on crop disease detection and classification from photos.

• Define the goals, including enhancing multi-crop disease detection, enabling real-time predictions, and increasing detection accuracy.

2. Dataset Preparation• Data Collection: Compile pictures of both healthy and sick crops from openly accessible datasets, agricultural research organizations, or by taking pictures in the field with cameras or unmanned aerial vehicles.

• Preprocessing: Make sure that pictures are the same size and format (e.g. G. in order to make it compatible with CNN architectures, resizing to 224x224 pixels.

• To improve diversity and lessen overfitting, perform data augmentation (rotation, flipping, cropping, and colour adjustments). Using dataset splitting, divide the dataset into sets for testing, validation, and training (e.g. G. 70% is allocated to training, 20% to validation, and 10% to testing. Use strategies like SMOTE or oversample minority classes to address class imbalance.

3.Model Selection

•Select CNN architectures that are appropriate for classifying images, like

VGG16 : A simple architecture with deep layers for the extraction of hierarchical features. ResNet is a residual learning framework designed to address problems with vanishing gradients. Initially, a multi-scale feature extraction model was created.

1)VGG16 Architecture

Simonyan and Zisserman (2014)[17] created VGGNet. It is a deep architecture which extracts features at low spatial resolution. VGGNet has two versions, namely VGG16 (with 16 wt. layers) andVGG19 (with 19 wt. layers). Large receptive fields in VGGNet have been substituted with consecutive layers of 3 × 3 convolutions with ReLU in between. The convolutional stride was fixed to 1 pixel. The padding of convolution layer input was maintained as 1 pixel and max-pooling was done with a stride of 2 over a 2 × 2-pixel window (Simonyan and Zisserman, 2014). The pile of convolutional layers was joined with 3fully connected layers and one softmax layer. VGGNet has 144 million parameters, of which approximately 124 million are used in the last 3Fully Connected layers. Therefore, if the fully connected layers could been laminated, the architecture efficiency could be enhanced. This step was taken in subsequent architectures replacing the first Fully Connected layer with a node layer using a method called average pooling (Varma and Das, 2018)[18].

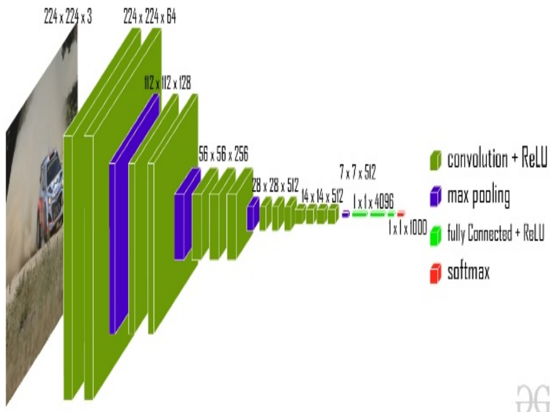

Fig.3 VGG16 Architecture

2)DenseNet Architecture

A novel method of joining layers in a neural network is presented by the deep learning architecture known as DenseNet (Densely Connected Convolutional Networks) . By establishing direct connections between each pair of layers, DenseNet differs from the conventional architecture in which each layer only receives input from the layer before it.

Synopsis of the DenseNet Architecture:

Input: A picture of size $H×W×C$H×W×C (height, width, channels). Multiple dense blocks make up the network, and each dense block is made up of multiple convolutional layers.

Every layer in a dense block creates a set of feature maps, which are then passed to the layer after it, which concatenates the current layer's output with the input from every layer before it.

Transition Layers: These are the layers that lie between dense blocks and help to control the number of feature maps and minimize their spatial size.

Convolutional layers are usually followed by pooling layers (such as average pooling) in transition layers. In order to reduce the spatial dimensions and produce a single vector per feature map, global average pooling is utilized following the last dense block.

Fully Connected Layer: Lastly, a fully connected layer and a softmax layer are applied to the global pooled feature map subsequently for classification.

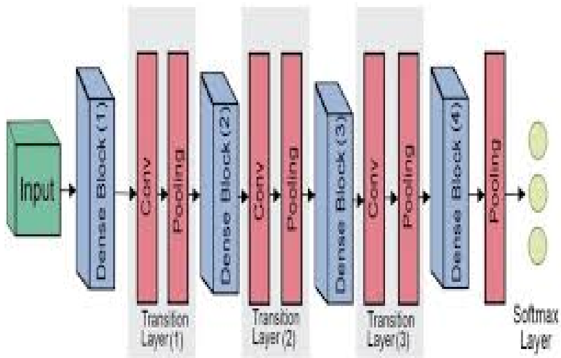

fig.4 DenseNet Architecture

An illustration of a dense block is Layer 1, which receives input feature maps. Feature maps as input and Layer 1's output are received by Layer 2. Layer 3: Gets input feature maps, Layer 1 output, and Layer 2output. A highly connected architecture is ensured by this pattern, which is repeated for every layer in the block.

•Transition Layer: To join dense blocks, transition layers are utilized. They have two primary functions: they reduce the quantity of feature maps and downsample the feature maps' spatial dimensions. This keeps the network's compactness and computational efficiency intact. In a typical transition layer, the feature maps are normalized using batch normalization. 1x1 Convolution: Cuts down on feature maps. Using average pooling, the spatial dimensions are downsampled.

•Growth Rate (k) One of DenseNet most important hyperparameters is the growth rate (k). In a dense block, it specifies how many feature maps are produced by each layer. More data is added at each layer with a higher growth rate, but the computational cost also rises. The capacity and performance of the network are impacted by the choice of k. The depth and number of layers are the main characteristics that set apart the various DenseNet variants. For example,

DenseNet-77, which has 121 layers, is renowned for striking balance between accuracy and computational efficiency. Perfect for jobs with moderate processing demands.

The 169-layer DenseNet-77 variant offers a more thorough feature extraction.

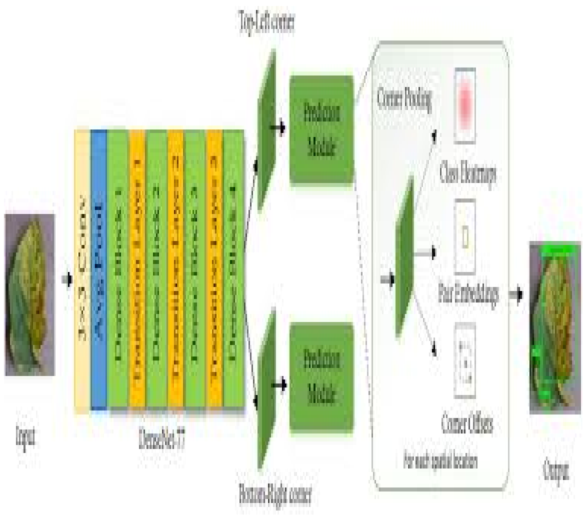

Fig.5 Pictorial depiction of the DenseNet-77-based model for the tomato plant leaf diseases classification.

Performance assessment metrics

Precision

The main metric of performance is the precision that studies the efficiency of the classifier. In most research articles, researchers appreciated their model according to precision. Accuracy is calculated using Equation (1):

Accuracy= (TP+TN)/(TP+TN+FP+FN)------------ (1)

True positive (TP) represents the number of correctly classified positive cases. Similarly, true negative (TN) represents the number of correctly identified negative cases. False positive (FP) is the number of actual negative cases classified as positive, while false negative (FN) is the number of actual positive cases classified as negative.

Sensitivity

Sensitivity is also known as True Positive Velocity (TPR) or Review. The ability of an ML model to accurately identify positive samples. Sensitivity is calculated using equation (2).

Sensitivity = TP/(TP + FN)--------------(2)

Accuracy

Accuracy is the ratio between the number of positive positive predictions and the total number of positive predictions. The accuracy is calculated using equation (3).

Precision = TP/(TP + FP)------------(3)

F1-Score

The F1-score is a metric to measure a test's accuracy in classification models. It is calculated from the precision and recall [3] using Equation (**4**):

$$F\,1\,Score = 2 \times \frac{Precision \times recall}{Precision + Recall} \quad (4)$$

Area under the ROC Curve (AUC)

The efficacy of a classification model can be assessed and compared via the area beneath the curve (AUC). It is a graph showcasing the ratio of true positives to f alse positives at different probability thresholds. This offers a clear method for encapsulating a model's co mprehensive performance. Generally, a subpar model features a notably diminished AUC value, reflecting the absolute disparity between predicted and actual o utcomes.

Matthews Correlation Coefficient (MCC)

The Matthews correlation coefficient (MCC) is a statistical measure that is able to accurately reflect the deficiency of any prediction in any dataset. In addition, it is a statistical rate that is more dependable and only gives a high score if the prediction performed well in all four categories of the confusion matrix (TP, FN, TN, and FP). MCC is calculated using Equation (**5**)

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (5)$$

4.CONCLUSION

Overall, these studies demonstrate the efficacy of CNN-based methods for crop disease detection while also highlighting areas for improvement, such as dataset diversity, model optimization, real-time adaptability, and cost-effective deployment. To choose the best deep CNN model to use in the detection of plant leaf diseases, comparison research has been done in this paper. Utilizing the crop leaf disease data set as training and testing data, deep

CNN models —DenseNet , VGG16, Inception V3, and ResNet152V2—were used. To save time and effort when training these models, transfer learning techniques are used. On the basis of transfer learning and DenseNet, we also suggested a classification model. The DenseNet model functions in our suggested model as the features extraction phase, which is followed by a CNN classifier. The outcomes demonstrate that the suggested model provides the greatest accuracy. By training certain additional model layers during transfer learning in addition to the player, we apply additional fine-tuning. The most accurate model is the one we've suggested. After that we developed a web based application that uses the proposed model to help farmers in diagnosing defected crop by uploading image and get the right diagnosis of the disease and also the recommended treatment in addition to more information about the disease. We intend to broaden our research in the future by using other CNNs that have already undergone multi-classification training. Adapt our suggested model to a wider range of crops and diseases. Update the developed tool to be more accurate in the treatment section and take in consideration some crop conditions and weather data for better diagnosing crop diseases that will benefit Indian farmers. In our experimental, the results shows that the proposed model achieves the highest training accuracy of 99.44% and validation accuracy of 98.70%

5. REFERENCES:

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