Deep Learning Based Techniques for Corn Plant Disease Detection Using UAV Imagery

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***Abstract*—Plant diseases have become a global concern as they pose a significant threat to food security. These diseases have the potential to cause damage to crops, reduce yields and compromise food quality. Moreover, the rapid spread of fungi, bacteria, and viruses can lead to widespread crop failures, creating food shortages, price increases, and ultimately, the risk of hunger. However, identifying plant diseases at the early stages remains challenging and time-consuming.Traditional methods of disease identification are often time-consuming and require manual inspection, which slows down timely actions and interventions.In recent years, deep learning-based techniques have given good results in plant disease detection. In this research paper, three deep learning models have been developed and compared for the identification of healthy and unhealthy corn plant leaves. The models include the Fully Convolutional Auto Encoder model, the Vision Transformer, along with a baseline CNN(Convolutional Neural Network) model. A data set of corn plant images acquired from UAV drone imagery is used for training and validating these models. The results indicate that the proposed Fully Convolutional Auto Encoder model achieved an accuracy of 95.09% outperforming both the Vision Transformer and CNN models. By leveraging deep learning-based techniques, such as the Fully Convolutional Auto Encoder model, the agricultural industry can benefit from improved disease detection and prevention. Early and accurate identification of plant diseases allows for timely interventions, such as crop protection measures, which can ultimately safeguard food security.**

***Index Terms*—Deep learning , Plant disease, Convolutional neural networks, Vision Transformer, Fully Convolutional Auto Encoder,UAV.**

I. Introduction

Corn is an important crop in India, serving food and raw materials for a variety of companies in the food industry. However, corn fields are prone to various diseases, which can lead to decrease in the outcome of the crop. Early detection of these diseases can increase our chances for the effective management and prevention of their spread. Deep learning-based methods have recently demonstrated considerable promise for automating plant disease identification. In this study, we explore the application of deep learning to the detection of Indian maize illnesses. We develop and train a deep learning model on the dataset which we created using images of healthy and diseased corn plants captured using a drone. Our model is able to accurately detect the disease. The performance of our model is evaluated using separate validation data and demonstrate its potential for use in automated disease detection systems for corn crops. With our study we are able to provide some important information about the use of deep learning for crop disease detection in India and highlights the potential for these techniques to contribute to improved crop productivity and sustainability.

A fungal disease caused by Bipolaris maydis called Southern corn leaf blight that affects corn plants. This disease is characterized by lesions on the leaves, that lead's to reduced photosynthesis and stunted growth which can decrease the yield. Southern corn leaf blight is a major concern for corn farmers in many parts of the world, including India , where it caused a significant epidemic in the 1970s. The effects of Southern corn leaf blight on corn plants are not well understood, and a further research on this can help us to understand better about the impact of the disease on yield and quality. In this paper, we investigate the effects of Southern corn leaf blight on corn plants, including its impact on yield, growth, and quality. Our analysis provides an overview about the effects of Southern corn leaf blight on corn plants and identifies key research gaps and priorities for future investigation.

Plant disease detection using Convolution Neural Networks (CNNs) is one of the emerging fields in the area of research that has gained a lot of importance in recent years. Study of plant disease detection using CNNs involves the development and application of different Deep learning algorithms to automate the detection of plant diseases. Our proposed approach has several advantages over traditional methods for disease detection in plants , which rely on humans and can be time-taking, subjective, and error-prone. In contrast, these Deep-learning techniques can automate the detection process and achieve high accuracy in identifying various diseases, such as fungal infections, viral infections, and nutrient deficiencies.

The study of plant disease detection using CNNs typically involves a review of existing literature in this domain. This literature includes research papers, conference proceedings, and books that discuss various aspects of CNN-based plant disease detection. The review covers topics such as the development of CNN architectures for plant disease detection, the creation and annotation of image datasets for training and validation, and the evaluation of CNN performance metrics such as accuracy, precision, recall, sensitivity, and specificity.The research utilizes a dataset of images of diseased and healthy plant leaves, and applies different deep learning models to classify the images.

The dataset in our research was built using UAVs where we have utilized drone imagery for data acquisition.Deep learning-based plant disease detection using UAV imagery has several advantages over traditional imagery. UAVs provide a distinct aerial perspective that enables the capturing of high-resolution images of crops from a variety of angles, resulting in greater coverage. UAVs can access difficult-to-reach areas, such as dense vegetation or remote fields, allowing for a more comprehensive crop health assessment. In addition, the adaptability and manoeuvrability of UAVs enable the acquisition of data on demand, reducing reliance on ground-based surveys and enabling real-time monitoring. Overall, UAV imagery improves the accuracy, efficiency, and scalability of plant disease detection, thereby enhancing crop management and yield.They offer valuable aerial perspectives for training models and analyzing data in various industries.

Overall, the background study explains the potential applications and benefits of deep learning techniques in the area of plant disease detection. That also includes discussions of how automated detection can improve crop production, reduce the chemicals and pesticides usage, and contribute to more sustainable agriculture practices.

The remainder of the paper is structured as follows, previous works related to deep-learning are discussed in Section II along with their use in agriculture sector. Section III discusses the concepts and methodology, whereas Section IV explains the proposed models architecture, their experimental results and a comparative analysis of the proposed models performance. Finally, Section V concludes our paper with experimental results.

II. RELATED WORKS

The plant disease detection and timely diagnosis are two crucial steps for ensuring crop health and maximizing agricultural productivity. In the recent times, the integration of deep learning techniques and unmanned aerial vehicles (UAVs) has showed good results in revolutionizing the field of plant disease detection.

With advancements in technology, the integration of deep learning techniques and UAV's has gained significant attention for plant disease detection. This section presents the related work in the area of disease detection in corn plant's using the InceptionV3 CNN architecture and drone photos, specifically employing the DJI Mavic 3 drone.

In our study, we experimented with three different techniques for corn plant disease detection namely Convolutional Autoencoder, Vision Transformer, and CNN baseline model. The Convolutional Autoencoder demonstrated the highest accuracy and efficiency among the three models, making it the primary focus of our research. The Vision Transformer model exhibited moderate performance, while the CNN baseline model achieved the least accuracy among the three models.

The main goal of this research was to develop a effective as well as accurate system for detecting corn plant diseases using the InceptionV3 CNN architecture and drone photos. By leveraging the power of deep learning and UAV technology, we aimed to contribute to the advancement of precision agriculture and enable farmers to take proactive measures in combating plant diseases, thereby minimizing yield losses and promoting sustainable agriculture practices.

Through this analysis, we aim to provide information of the performance and efficiency of the proposed approach for corn plant disease detection using drone photos and the InceptionV3 CNN architecture.

The related work presented in the area of disease detection for corn plant using the InceptionV3 CNN architecture and drone photos, specifically with the DJI Mavic 3 drone, demonstrates the growing interest in utilizing UAV imagery and deep learning techniques for precision agriculture.

These studies highlight the effectiveness of deep learning models, including CNN architectures, in accurately detecting the plant diseases. The integration of UAVs and deep learning techniques provides a promising avenue for non-invasive and efficient disease monitoring in corn crops, contributing to enhanced agricultural practices and improved crop management.

This paper [1] emphasizes the detection of diseases in tobacco plants using neural networks applied to UAV images, showcasing the efficacy and effectiveness of deep learning techniques in disease detection in plants. It highlights the importance of dataset creation, robust feature extraction, and classification methods for accurate plant identification.

Although it does not directly address disease detection, the study underscores the significance of these techniques in accurately identifying plants using UAV imagery.

As mentioned in [2] With the aid of UAV photos, it proposes a deep learning-based method for automatically identifying soybean leaf illnesses, illustrating the potency and utility of deep convolutional neural networks in disease identification. In order to achieve high accuracy in illness classification, it emphasises the importance of large-scale datasets, dataset quality, transfer learning, and model evaluation metrics.

In the article [3] It proposes a methodology for calculating the winter wheat's leaf area index (LAI) using UAV data and CNNs. While it does not specifically focus on disease detection, it highlights the potential of CNNs and UAV imagery in quantifying crop growth parameters. The study emphasizes the importance of appropriate image preprocessing techniques and CNN architectures for accurate LAI estimation.

According to [4] a fully convolutional autoencoder for change detection in UAV aerial imagery, emphasizing the effectiveness of deep learning methods for identifying changes in crop growth. While not directly focused on plant disease detection, these changes can indicate disease presence. The paper highlights the significance of unsupervised learning, data augmentation, image differencing, and model optimization for achieving accurate change detection.

As Stated in [5] This research paper proposes a CNN-based approach and methodology for accurately identifying soybean foliar diseases by using UAV images. It highlights the potential and significance of utilizing UAV imagery and deep learning techniques in disease detection for soybean crops. The study emphasizes the importance of fine-tuning pre-trained models, employing multi-scale image analysis, and ensuring accurate labeling and dataset quality to improve disease recognition.

In [6] The paper presents a deep learning-based method for counting corn plants using UAV images, emphasizing the importance of accurate object localization and dataset balancing. It highlights the application of deep learning and UAV imagery in assessing crop population, which can indirectly aid in disease identification. The study considers challenges such as occlusion and varying growth stages, and emphasizes that accurate plant counting can indirectly aid in disease assessment.

According to [7] demonstrates the effectiveness of the proposed methodology for accurately identifying and monitoring corn fields using UAV imagery. The study discusses the benefits of using drones to capture high-resolution images, emphasizing their potential for disease detection and management. It also highlights the importance of image analysis algorithms and the integration of drone technology into precision agriculture practices.

In [8] A CNN-based approach for plant disease detection has been proposed in [8], emphasizing the significance of large-scale datasets, transfer learning, and model optimization for improved disease classification. The study demonstrates the effectiveness of the proposed methodology in accurately detecting plant diseases in different crops, which includes corn, showcasing the power of deep-learning methods in the field of agriculture.

It is mentioned in [9] a multi-condition training approach for deep convolutional neural networks (CNNs) to enhance the robustness of plant disease detection. Although the focus is on general plant diseases, the methodology helps us in choosing a simple baseline cnn model for corn plant disease detection. The paper introduces techniques for handling variations in lighting, background, and other conditions, which can be valuable for addressing similar challenges in corn disease detection.

According to [10] While the focus is on SAR images, the use of deep convolutional autoencoders can provide insights for feature extraction in corn disease detection. The paper's approach to learning discriminative features can be beneficial for enhancing the detection capabilities of the corn disease detection system.

As stated in [11] the focus is on leaf diseases, the methodology can be extended to corn plant disease detection. The paper demonstrates the effectiveness of using deep convolutional autoencoders to learn representative features, which can contribute to improved accuracy and robustness in corn disease detection.

It is mentioned in [12] the prediction of canopy-averaged chlorophyll content in pear trees using convolutional autoencoders on hyperspectral data. While the plant species and application differ, the use of convolutional autoencoders for feature extraction can be applicable to corn plant disease detection. The paper's methodology for leveraging hyperspectral data and autoencoders can provide insights into optimizing feature extraction techniques for corn disease detection using drone images

According to [13] the effectiveness of using hyperspectral data to capture detailed spectral information, which is then processed through CNNs for accurate disease detection. The research showcases the potential of hyperspectral imaging and deep learning techniques in improving the efficiency and accuracy of plant disease diagnosis. The proposed methodology contributes to advancements in precision agriculture and can aid in the timely identification and management of plant diseases.

In [14] a deep convolutional neural network (CNN)

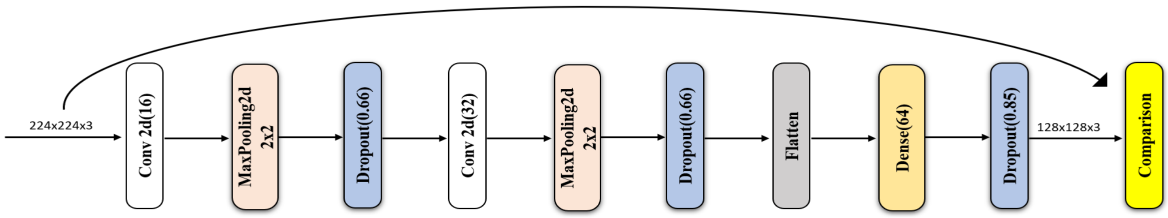


Fig. 1: **Flow Chart representing CNN architecture**

(a) (b) (c) (d)

Fig. 2: Healthy and Unhealthy Plant images from Dataset

architecture trained on a large dataset of leaf images to accurately detect and classify plant diseases. The paper demonstrates the potential of deep learning models in achieving high accuracy in plant disease identification, providing valuable insights for developing similar disease detection systems using CNNs. The approach contributes to the advancement of automated plant disease detection, facilitating timely interventions and improving crop management practices.

III. Methodology

In this section, we are going to explain the steps that we have followed in our research work. Our research design flows by image based research which includes data acquisition, data pre-processing and creating train and validation data sets. All these steps are explained in detail later in this section.

A. Data-acquisition

In every research work data acquisition is a critical step, because having the correct data set is very important for designing an efficient model. Unlike traditional process of acquiring data of plants using DSLR or any other means, in our study we have utilised a UAV(Unarmed Aerial Vehicle) to capture the images of corn plants.

We have utilized DJI Mavic 3 UAV which has the ability to record high-resolution 4k videos at 120 fps. This drone has been flew over the field above 40 meters altitude for capturing the videos above the plants. We have captured these videos in all possible directions in order to have the maximum possibilities for detecting plant diseases.

To ensure maximum area of the field is covered, we flew the drone in a zig zag model. These video footage is then converted into images by using a python code that captures each frame in the video and gives us a folder containing images of field for the purpose of pre-processing and disease detection, which will be explained in the coming sections. Fig 2 shows the images of both classes namely healthy and unhealthy, which are captured in aerial view by the UAV.

B. Data Pre-processing

Pre-processing the data is an important step in analysis of the dataset collected using a drone for plant disease detection. The first step we have followed is to remove duplicate images that are out of focus or contain motion blur because these images can negatively impact the results. Then those images are converted into the required shapes that is their pixels are reduced to the required number. In our research work a comparison between 3 different techniques has been carried out, which will be explained in the coming sections. All these techniques had been implemented on colour images with RGB metrics.

C. CNN Architecture

Baseline CNN architectures typically consists of a stack of convolution layers, followed by pooling layers and fully connected layers. These CNN architectures has the ability to classify images based on their features and by analysing the input image patterns which will be learned from the training

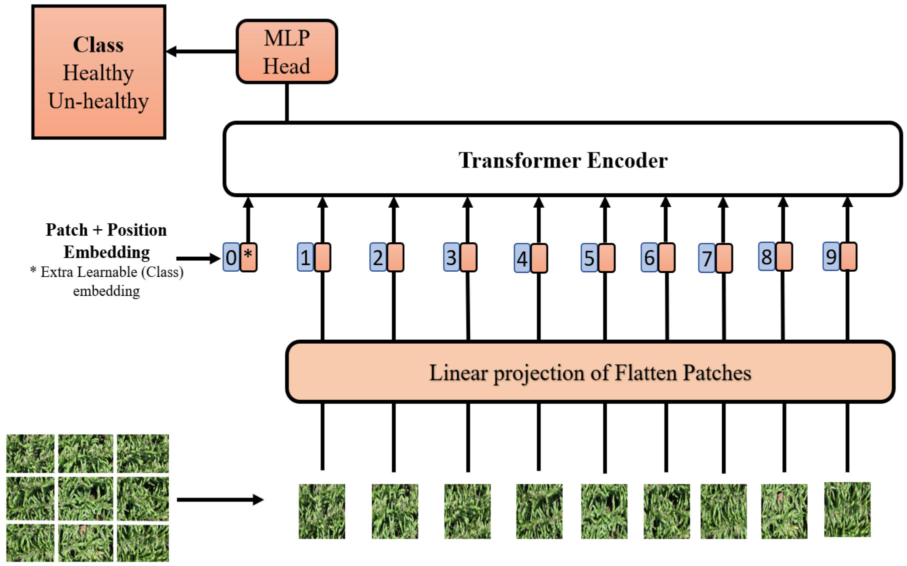


Fig. 3: Vision Transformer Architecture

data. This abilities of the CNN are very much helpful in tasks like plant disease detection. As mentioned we have designed a baseline CNN architecture to detect plant disease from images.

Input layer, Convolution layer, Pooling layer and fully connected layer along with an output layer are the fundamental parts of a Baseline CNN architecture. Each and every layer has its own and unique contribution to the successful implementation of the task assigned to the CNN model.

A Convolution layer is used to convert a input 3D tensor usually an image into a Feature map tensor by applying a set of filters to it usually called kernel's. The mathematical representation can be give as

$$H(I,J,K) = Activation(\sum(M,N,O)X(I+M,J+N,O)* W(M,N,O,K)+b(K)) \tag{1}$$

This convolutional layer will be connected to a pooling layer. A pooling layer will reduce the spatial dimensions of the Feature map extracted by convolutional layer which retains the most useful information to generate a pooled feature map tensor. Mathematically pooling layer can be defined as:

$$P(i,j,k) = max(H(i*s, j*s, k)) \tag{2}$$

A fully connected layer consists of neurons, in which each neuron has its own weight and bias term. These neurons are utilized to extract a vector of logits representing the class probabilities from a flattened vector representing the features from its previous layers.

$$Z = F \cdot W + b \tag{3}$$

Like any other CNN architectures we also have started our CNN model with an input layer which takes the images of size(224,224,3) representing the width, height and color channels of the images. These convolution layers are building blocks of any CNN architecture, as they consist of multiple filters and kernels which convolve with the input data to extract the required features or patterns. Each filter calculates the dot product of its weights and a small region of the input, which produces a feature map representing the presence of certain features or patterns. These convolutional layers are typically followed by activation functions, such as Re-LU (Rectified Linear Unit), to introduce non-linearity.

After a set of convolution layers a pooling layer will often be implemented to reduce the spatial dimensions of the extracted features by safe guarding the related features. Max-pooling is the most frequently used pooling technique in which the maximum value within a local neighborhood is selected to form a down sampled representation.

As explained above, even our model consists of two sets of convolutional layers with a max pooling and dropout applied after each set.The second set of convolutional layers output is passed through flatten layer and connected to a fully connected layer with dropout. Fully connected layers are similar to those in a traditional multi-layer perception (MLP) neural network, which learn to classify the high-level features extracted by the previous layers and make predictions based on the learned representations. Finally, the output layer with softmax activation is added to perform the classification into two classes.

Fig-1 shows all the layers in the CNN architecture. The input layer takes the input image in size 224x224x3, which then undergoes through multiple Convolution layers, Max pooling layers and Dropout Layer to extract necessary features for classification along with Flatten and Dense Layers to avoid over-fitting. At last the model will be compiled with input images as the input given to the model and output labelled as the output of the model with 'categorical-crossentropy' as loss function.

D. Vision Transform

Vision Transformer (ViT) is a deep-learning architecture. Unlike traditional convolution neural network(CNN) architectures, Vision transformer is a transfer-based model which is originally introduced for natural language processing tasks. ViT divides the input images into fixed-size patches and treats them like tokens, just like words in a sentence. These tokens are then feed into transform encoder in linear arrangement.

The main idea behind the Vision Transformer is to leverage the power of the self-attention mechanisms to capture long-range dependencies and relation patterns between these image patches or tokens, as shown in Fig 3.

Multiple layers of self-attention and feed-forward neural networks are embedded in the transformer encoder. Self-attention capability of the model allows it to capture long-range dependencies between patches, while the feed-forward networks apply non-linear transformations to the features extracted. The output of the transformer encoder is a sequence of feature vectors representing different patches. All these steps of vision transformer are shown in Fig 3 for better understanding.

To make predictions, a classification head is added on top of the transformer encoder. This head takes the final feature vector as input and produces class probabilities or regression outputs depending on the task at hand. During training, the ViT model is optimized using supervised learning techniques, such as cross-entropy loss.

In our model we had utilized the pre-trained VGG-16 architecture to design the Vision Transformer and initialized the model with the weights of Image-net. We will be getting a 4D tensor as output from the vision transformer and to convert it into a 2D tensor, a Flatten layer is added after the VGG-16 layer along with a fully connected dense layer which consists of 28 units and a ReLU activation function. The process of extracting more abstract features from the flatten layer output is carried out by the fully connected dense layers. To prevent over-fitting of data a dropout layer with a rate of 0.85 is added to the model design.

To produce the classification probabilities for the two classes, an output layer with 2 units and a softmax activation function is added, then the model is compiled with optimizer set to Adam and Binary cross-entropy as loss function along with additional metrics to evaluate the performance of the model.

E. Auto Encoder

Auto-encoder is a type of CNN architecture which is mainly utilized for unsupervised learning and tasks like feature extraction. An Auto-encoder mainly consists of a encoder and a decoder blocks. The encoder component maps the given input images to a lower-dimensional representation and the decoder component is responsible for reconstructing the original image from the lower-dimensional representation.

The main principle of an auto encoder to is train its encoder-decoder pair to reconstruct the input images with minimal reconstruction error. With minimizing this we can improve the auto-encoder's ability of capturing the salient patterns and features in the input images.

Our auto encoder model is defined using the Keras functional API. It is designed with an input layer, followed by several convolutional layers which are activated by ReLU activation function to introduce non-linearity and pooling layers to reduce the spatial dimensions of images. All these layers are used to encode the input images into a set of features that can be used to reconstruct the image by the decoder.

This encoded representation of image is then processed through a series of convo2D and up-sampling layers which will increase the spatial dimensions of these features to reproduce the input image. The architecture of the auto encoder is symmetric, with the encoded layer acting as the bottleneck.

All of these steps explained above are represented in detail in Fig 4, which depicts that the Encoder is designed using a set of Convolutional layers in which two layers consists 8 neurons and one layer consisting 16 neurons. Along with a set of Max-pooling layers with (2X2) dimensions. The output of this encoder is a low dimensional encoded image which is further reconstructed by the decoder, whose design is similar to that of the encoder with a flatten layer added at the end of it. After the flatten layer we will get the reconstructed image, which will be compared with the input image to calculate the reconstruction error of the model.

After defining the model architecture, the code compiles the auto encoder model. The optimizer is set to Adam, and categorical cross-entropy is used as loss function to measure the re-construction loss, which should be as minimum as possible for the model to be efficient. Additionally, accuracy is chosen as a metric to evaluate the models efficiency.

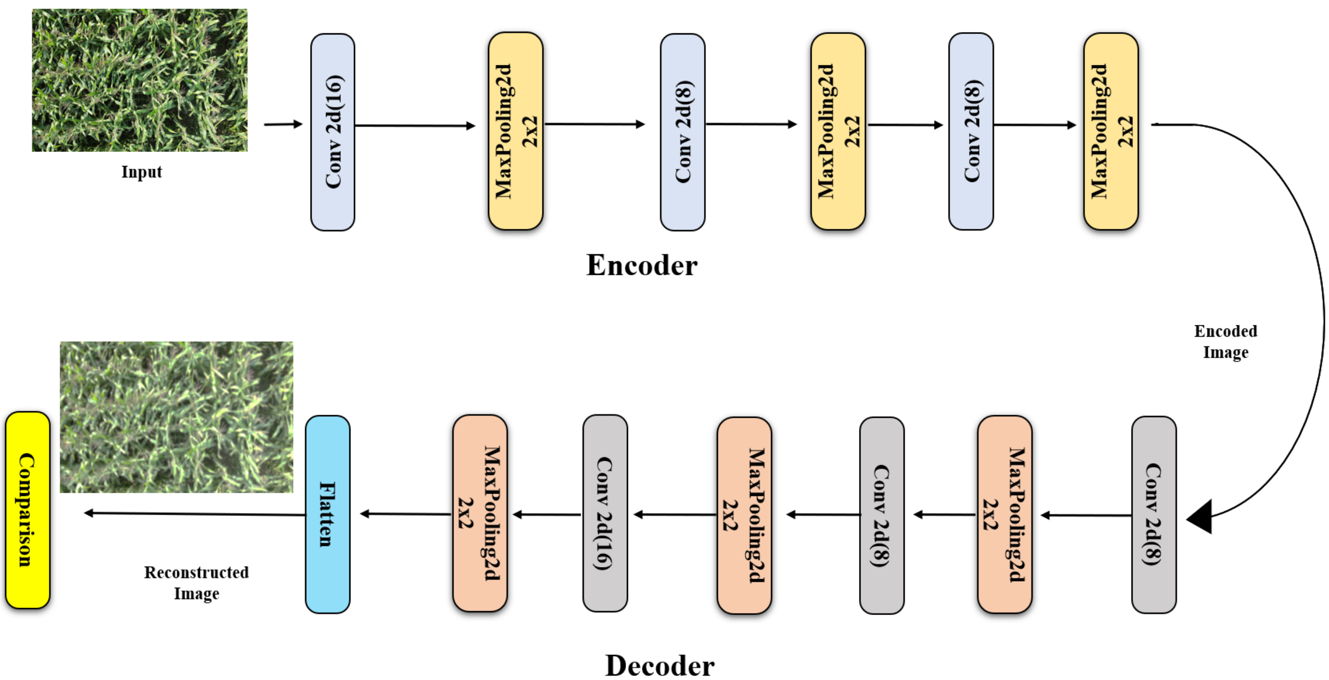


Fig. 4: **Flow Chart representing Fully Convolutional Auto Encoder Architecture**

Finally, the convolutional auto-encoder is trained using the fit function. The training data set is passed to the function, and the training of the model is carried out for a specified number of epochs (in this case, 4). As mentioned in all of the three models Convolution layers.

F. Metrics

*1) **Accuracy**:* Accuracy serves as a commonly employed metric for assessing the performance of classification models. It quantifies the ratio of accurate predictions made by the model to the overall number of predictions. The mathematical representation of accuracy can be defined as the proportion of correct predictions divided by the total predictions.:

$$Accuracy = \frac{T.P + T.N}{T.P + T.N + F.P + F.N} \tag{4}$$

*2) **Loss**:* Loss can be defined as the quantitative measure of the model's performance or the discrepancy between predicted and true values. It is a key component in training models and optimizing their parameters. There are various types of loss function which can be used based on the purpose of the model. In our research work we had utilized Binary cross-entropy and Categorical cross-entropy as Loss functions.

*3) **Binary Cross-entropy**:* The Binary Cross Entropy loss is frequently employed in binary classification tasks. It computes the discrepancy between the actual class labels and the predicted class probabilities. The formula for Binary Cross Entropy can be expressed as follows:

$$L_{\text{Binary Cross-entropy}} = -(y \log(p) + (1 + y) \log(1 - p)) \tag{5}$$

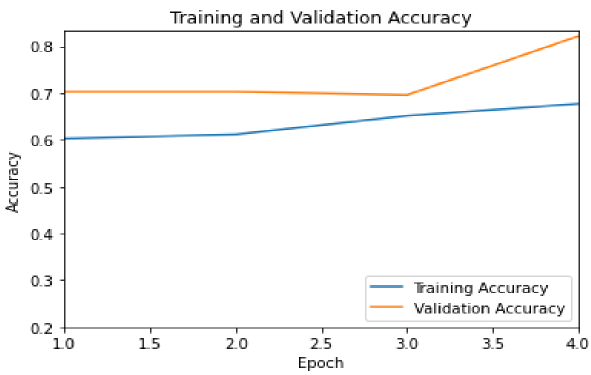
*4) **Categorical Cross-Entropy**:* The Categorical Cross Entropy loss is widely utilized in multi-class classification scenarios. It measures the difference between the actual class distribution and the predicted class probabilities. This loss function is commonly employed to evaluate the variation between the true class distribution and the predicted probabilities in multi-class classification problems.The formula for Categorical Cross Entropy is as follows:

$$L_{\text{Categorical Cross-Entropy}} = -\sum_{i=1}^{N} y_{\text{i}} \log p(i) \tag{6}$$

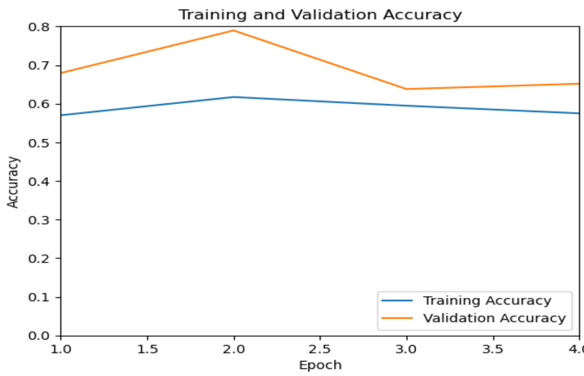
IV. Experimental Results

This section provides a comprehensive analysis and discussion of the results achieved using the proposed approach.

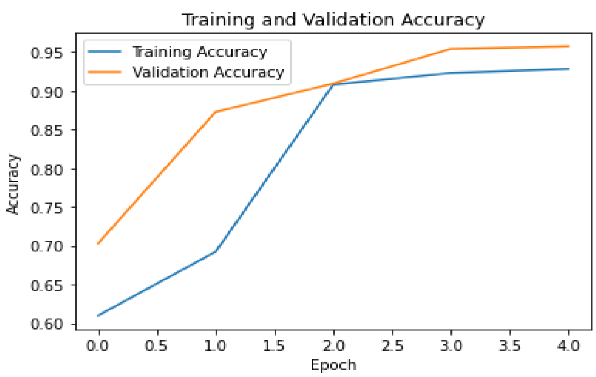
Table I thoroughly examines and elaborates on the validation outcomes attained through the proposed approaches.The proposed models were trained and validated using a dataset acquired by UAV imagery over a span of four



(a) CNN Architecture

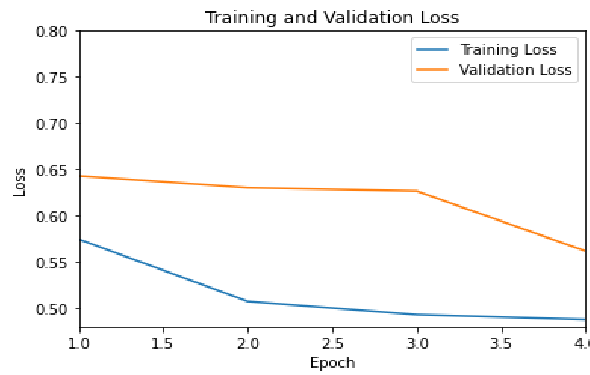


(b) Vision Transformer

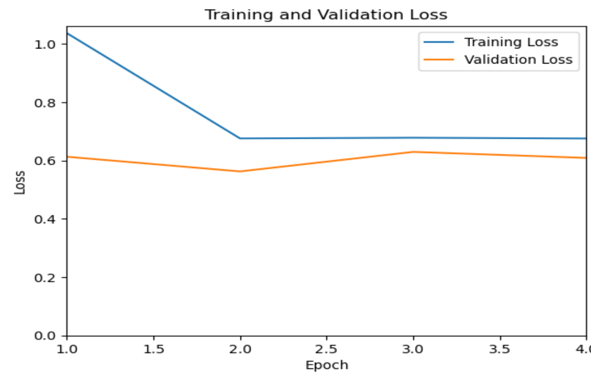


(c) Auto Encoder

Fig. 5: Accuracy of CNN vs Vision Transformer vs Auto Encoder



(a) CNN Architecture



(b) Vision Transformer

(c) Auto Encoder

Fig. 6: Loss Metric of CNN vs Vision Transformer vs Auto Encoder

epochs.

The proposed CNN model has attained its highest validation accuracy of 82.1% at a loss rate of 0.5613 in it's ultimate epoch. Fig 5(a) gives an overview between train and validation accuracy's of the convolution neural network model with number of epochs on x-axis and Accuracy on the y-axis as parameters.Fig 6(a) gives an overview between training loss and validation Loss of the same model with number of epochs on x-axis and parameter loss on the y-axis as parameters. In Fig 6(a) as we pass by the epochs,the decrease in Loss is evident at the 4th epoch which subsequently resembles increase in accuracy which can be witnessed in Fig 5(a) at epoch 4 and this is the highest accuracy attained by the model overall.

Similarly, the proposed Vision transformer has acquired a validation accuracy of 78.97% at a loss rate of 0.5629.Fig 5(b) presents an overview on training and validation accuracy and Fig 6(b) presents an overview on the training and validation Loss of the vision transformer model.

The proposed Fully Convolutional Auto encoder model has achieved an accuracy of 95.09% at Loss rate of 0.1442.

TABLE I: PERFORMANCE METRICS

	Metrics	epoch1	epoch2	epoch3	epoch4
CNN	Loss	0.6427	0.6299	0.6262	0.5613
	Accuracy	70.3%	70.3%	69.6%	82.1%
Vision Transformer	Loss	0.6133	0.5629	0.6299	0.6093
	Accuracy	67.9%	78.9%	63.7%	65.1%
Auto Encoder	Loss	0.5610	0.3397	0.2310	0.1442
	Accuracy	70.31%	91.52%	94.02%	95.09%

Fig 5(c) depicts the relation between validation and training accuracy's of the model and in the same way Fig 6(c) depicts the correlation between loss values. Overall,the Fully Convolutional Auto encoder has achieved desired results among all the proposed models with an accuracy of 95.09%.

V. Comparitive Analysis

By analyzing Table II it is evident that the Fully convolutional Auto encoder model has outperformed the traditional CNN and Vision transformer models. The table depicts the accuracy attained by each model. The Fully convolutional auto encoder has attained an accuracy of 95.09% whereas the CNN and vision transformer models have attained an accuracy of 82.19% and 78.97% respectively.

Table I depicts the performance metrics of all the models namely the CNN,Vision Transformer and Fully Convolutional Auto Encoder Model. All the models have been trained for 4 epochs . During the training of an autoencoder, the binary cross-entropy loss function, which measures the reconstruction error between the input image and the reconstructed image, has typically decreases as each epoch progresses. Initially, the autoencoder may struggle to accurately reconstruct the data, resulting in a higher loss. However, as the training proceeds, the model adjusts its internal parameters through techniques like back propagation and gradient descent, improving its ability to capture relevant features and generate more accurate reconstructions. Consequently, the loss gradually decreases, indicating a better fit between the input image and the reconstructed image. The rate of loss reduction can vary based on factors like data complexity, architecture, optimization algorithm, and dataset size. Monitoring the loss is crucial to ensure convergence towards a desirable solution. This helps the Auto encoder model to attain a stable accuracy.

The proposed Fully convolutional auto encoder model has attained 95.09% accuracy at a loss of 0.1442 which can considered as very low loss rate when compared within its concurrent epochs and also when compared with the CNN and vision transformer models. CNN model attained its best accuracy 82.19% at a loss of 0.5613 whereas the vision transformer model model attained its best accuracy 78.97% at a loss of 0.5629.Fig 5 and Fig 6 gives a complete overiew on the accuracy and loss attained by the CNN,Vision Transformer and Auto Encoder models respectively over their training and validation datasets.

TABLE II: Accuracy Measurment

Model	Accuracy
CNN	82.19%
Vision transformer	78.97%
Auto Encoder	95.09%

VI. Conclusion

Results obtained by our Experimental analysis allows us to conclude that implementation of Deep Learning techniques in the agriculture sector has given good results in terms of Disease detection. Based on our thorough analysis, we can deduce that the Fully Convolutional Auto Encoder methodology presented in this paper has achieved a validation accuracy of 95.09%, surpassing all other deep learning techniques. Our study further suggests that implementing deep learning models for plant disease detection can mitigate the impact of diseases on crop yields, thereby promoting increased production.

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References

[1] Z. Fan, J. Lu, M. Gong, H. Xie and E. D. Goodman, "Automatic Tobacco Plant Detection in UAV Images via Deep Neural Networks," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 11, no. 3, pp. 876-887, March 2018, doi: 10.1109/JSTARS.2018.2793849. .

[2] E. C. Tetila et al., "Automatic Recognition of Soybean Leaf Diseases Using UAV Images and Deep Convolutional Neural Networks," in IEEE Geoscience and Remote Sensing Letters, vol. 17, no. 5, pp. 903-907, May 2020, doi: 10.1109/LGRS.2019.2932385. .

[3] L. Wittstruck, T. Jarmer, D. Trautz and B. Waske, "Estimating LAI From Winter Wheat Using UAV Data and CNNs," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 2503405, doi: 10.1109/LGRS.2022.3141497.

[4] D. B. Mesquita, R. F. d. Santos, D. G. Macharet, M. F. M. Campos and E. R. Nascimento, "Fully Convolutional Siamese Autoencoder for Change Detection in UAV Aerial Images," in IEEE Geoscience and Remote Sensing Letters, vol. 17, no. 8, pp. 1455-1459, Aug. 2020, doi: 10.1109/LGRS.2019.2945906.

[5] E. Castelão Tetila, B. Brandoli Machado, N. A. Belete, D. A. Guimarães and H. Pistori, "Identification of Soybean Foliar Diseases Using Unmanned Aerial Vehicle Images," in IEEE Geoscience and Remote Sensing Letters, vol. 14, no. 12, pp. 2190-2194, Dec. 2017, doi: 10.1109/LGRS.2017.2743715.

[6] J. Kolli, D. M. Vamsi and V. M. Manikandan, "Plant Disease Detection using Convolutional Neural Network," 2021 IEEE Bombay Section Signature Conference (IBSSC), Gwalior, India, 2021, pp. 1-6, doi: 10.1109/IBSSC53889.2021.9673493.

[7] S. Rachmawati et al., "Application of Drone Technology for Mapping and Monitoring of Corn Agricultural Land," 2021 International Conference on ICT for Smart Society (ICISS), Bandung, Indonesia, 2021, pp. 1-5, doi: 10.1109/ICISS53185.2021.9533231.

[8] B. T. Kitano, C. C. T. Mendes, A. R. Geus, H. C. Oliveira and J. R. Souza, ”Corn Plant Counting Using Deep Learning and UAV Images,” in IEEE Geoscience and Remote Sensing Letters, doi: 10.1109/LGRS.2019.2930549.

[9] R. S. Yuwana, E. Suryawati, V. Zilvan, A. Ramdan, H. F. Pardede and F. Fauziah, ”Multi-Condition Training on Deep Convolutional Neural Networks for Robust Plant Diseases Detection,” 2019 International Conference on Computer, Control, Informatics and its Applications (IC3INA), Tangerang, Indonesia, 2019, pp. 30-35, doi: 10.1109/IC3INA48034.2019.8949580.

[10] J. Geng, J. Fan, H. Wang, X. Ma, B. Li and F. Chen, ”High-Resolution SAR Image Classification via Deep Convolutional Autoencoders,” in IEEE Geoscience and Remote Sensing Letters, vol. 12, no. 11, pp. 2351-2355, Nov. 2015, doi: 10.1109/LGRS.2015.2478256.

[11] K. Trang, L. TonThat and N. G. Minh Thao, ”Plant Leaf Disease Identification by Deep Convolutional Autoencoder as a Feature Extraction Approach,” 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Phuket, Thailand, 2020, pp. 522-526, doi: 10.1109/ECTI-CON49241.2020.9158218.

[12] S. Paul, V. Poliyapram, N. İmamoğlu, K. Uto, R. Nakamura and D. N. Kumar, ”Canopy Averaged Chlorophyll Content Prediction of Pear Trees Using Convolutional Autoencoder on Hyperspectral Data,” in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 1426-1437, 2020, doi: 10.1109/JSTARS.2020.2983000.

[13] H. Amin, A. Darwish, A. E. Hassanien and M. Soliman, ”End-to-End Deep Learning Model for Corn Leaf Disease Classification,” in IEEE Access, vol. 10, pp. 31103-31115, 2022, doi: 10.1109/ACCESS.2022.3159678.

[14] M. Agarwal, V. K. Bohat, M. D. Ansari, A. Sinha, S. K. Gupta and D. Garg, ”A Convolution Neural Network based approach to detect the disease in Corn Crop,” 2019 IEEE 9th International Conference on Advanced Computing (IACC), Tiruchirappalli, India, 2019, pp. 176-181, doi: 10.1109/IACC48062.2019.8971602.

[15] Picek, Lukas & Sulc, Milan & Matas, Jiri & Heilmann-Clausen, Jacob & Jeppesen, Thomas & Lind, Emil. (2022). Automatic Fungi Recognition: Deep Learning Meets Mycology. Sensors. 22. 633. 10.3390/s22020633.