Revolutionizing Plant Disease Detection in Leaves: An Innovative Hybrid ABOCNN Framework for Advanced and Accurate Identification

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***Abstract*—Plant diseases are a persistent threat to the global agricultural economy, compromising food supply and security. Accurate and early diagnosis is vital for effective agricultural management. This study addresses this gap by introducing a better approach for identifying plant diseases in leaves: the Integrated Hybrid Attention-Based One-Class Neural Network (ABOCNN) System. The system uses deep learning and domain-specific information, as well as powerful neural networks and attention processes, to extract features unique to a certain ailment while excluding irrelevant data. By dynamically focusing on prominent areas in leaf images, the proposed methodology obtains an impressive 99.6% accuracy, beating both traditional approaches and cutting-edge deep-learning approaches by an average of 12.7%. The practical use of this strategy has a significant influence on crop yield and agricultural sustainability. Attention maps increase interpretability and help individuals comprehend more fully how decisions are made. The system, written in Python, is precise, scalable, and adaptable, making it a helpful tool for a wide range of agricultural applications combining multiple plant species and disease classifications. With an incredible 99.6% accuracy rate, the Integrated Hybrid ABOCNN Technology provides an innovative method for diagnosing plant diseases, outperforming conventional approaches by 12.7%. Attention maps increase interpretability and give important information about the model's decision-making processes.**

Keywords*—Convolutional Neural Network (CNN); attention model; leaf disease detection; attention-based one-class neural network; crop production

I. Introduction

Plant leaf detection refers to the process of identifying and analyzing the characteristics of leaves in plants. Leaves are vital components of plants, playing a crucial role in photosynthesis, respiration, and transpiration. By detecting and understanding various leaf attributes, such as shape, size, color, and texture, researchers, botanists, and agriculturalists can gain valuable insights into plant species identification, health assessment, disease detection, and growth monitoring. Leaf detection has traditionally been a manual and time-consuming task, requiring experts to visually inspect and classify leaves based on their features [1]. However, automatic leaf recognition is now more practical and precise because to developments in neural networks, algorithmic learning, and computational imaging methods. By utilizing sophisticated algorithms and neural networks, leaf detection systems can analyze digital images or live video feeds to identify and segment leaf regions from complex backgrounds. These systems can also extract relevant features from the detected leaves, enabling further analysis and classification [2]. The applications of plant leaf detection are diverse and impactful. In agriculture, leaf detection can aid in crop management, enabling early detection of diseases, nutrient deficiencies, or pest attacks. It can assist in optimizing irrigation, fertilization, and overall plant health monitoring. Additionally, leaf detection has significant implications in environmental conservation, as it can aid in species identification, biodiversity assessment, and ecosystem monitoring [3]. Overall, plant leaf detection offers an efficient means to study and understand the characteristics of leaves, providing valuable insights into plant health, growth, and species identification. With continued advancements in technology, this field holds great potential for revolutionizing plant science, agriculture, and ecological research [4].

A cutting-edge method for automatically identifying and detecting leaves from plants is foliage identification using deep learning, which makes use of the capabilities of networks. Deep learning models, especially CNN, have demonstrated outstanding ability in image analysis and identification, which makes them suitable for jobs requiring the detection of leaves. In order to distinguish leaf in the foreground and correctly identify their existence in an image, the subject learns to identify patterns, characteristics, and architectures that are exclusive to leaves. Intricate nuances and changes in leaf attributes, like as form, texture, venation patterns, and color, may be captured by deep learning models since they are excellent at autonomously generating hierarchical representations of data. They can handle complicated leaf shapes and identify between many plant species quite effectively [5]. The key benefit of leaf identification using deep learning is its ability to generalize well to unseen data. Once trained, the model can efficiently process new leaf images and accurately identify leaves even in diverse environments and under varying lighting conditions. The applications of deep learning-based leaf detection are vast. It can assist botanists and researchers in plant species identification, enabling quick and reliable classification of leaves. It also plays a crucial role in plant disease diagnosis and monitoring, as the detection of abnormal leaf patterns or discoloration can indicate potential health issues [6]. Additionally, deep learning-based leaf detection contributes to precision agriculture by enabling automated crop monitoring, yield estimation, and targeted interventions for optimizing plant health and growth. However, it's important to note that deep learning-based leaf detection requires a large and diverse dataset for training the model effectively. The initial training dataset's reliability and accurate representation have an important effect on the model's accuracy and generalizability. Plant leaf diseases represent a severe threat to crop production, efficiency in agriculture, and the availability of food [7]. These illnesses need to be correctly recognized and categorized early on in order to receive quick therapies and effective management techniques. Due to their shown high effectiveness in image recognition tasks, algorithms that utilize deep learning are especially well-suited for the diagnosis and classification of diseases of plant leaves. A sophisticated hybrid approach called ABOCNN has been created in this situation, fusing the benefits of several deep learning architectures [8].

The ABOCNN framework integrates the power of CNN and attention-based mechanisms to enhance disease detection and classification accuracy. CNNs are recognized for their capacity to autonomously acquire and extract significant characteristics from images. Attention mechanisms concentrate on critical regions, allowing the network to give better consideration to disease-specific patterns in leaf images [9]. The key advantage of the ABOCNN framework lies in its ability to handle complex and diverse disease patterns, including subtle variations in leaf textures, discoloration, lesions, and other disease-related characteristics. By integrating CNNs' feature extraction capacities with attention processes, the framework may efficiently collect both global and local disease-related information, permitting precise and accurate plant leaf disease diagnosis [10]. The suggested paradigm has important effects on crop management, farming, and the pathology of plants. It provides a quick and automated method for identifying and categorizing plant leaf diseases, enabling early intervention with targeted therapies. In turn, this aids agronomists and farmers in making educated choices, allocating resources efficiently, and reducing crop losses. In conclusion, the ABOCNN framework provides a cutting-edge method for the identification and categorization of plant leaves using deep learning. It improves the dependability and precision of disease identification by merging CNNs and attention processes, which helps to create more efficient and environmentally friendly agricultural practices [11].

The key contributions of this paper are as follows:

- With a sophisticated hybrid ABOCNN architecture as the foundation, the study introduces a revolutionary deep learning technique that results in a significant increase in accuracy.
- The Attention Mechanism enhances the capacity of the model to identify disease-specific characteristics in leaf images. The method enhances accuracy and making decisions by constantly attributing significance to geographical elements.
- Attention maps enhance the comprehensibility of the suggested method. These maps provide users with useful knowledge into the procedure and enable them to better understand the procedure for making decisions.
- The hybrid ABOCNN model is adaptable and scalable, making it suitable for usage with a wide range of plant species and diseases. Because of its adaptability, it may be employed in a variety of agricultural applications.
- The finding signifies a substantial advancement in the treatment of agricultural conditions using deep learning. The hybrid ABOCNN approach has the capability to significantly enhance agricultural results by transforming plant disease detection and intervention techniques.

The approached paper's manuscript is structured as follows: Several similar works are reviewed in Section II. Information on the problem statement is given in Section III. The planned ABO-CNN is detailed in depth in Section IV. In Section V, research findings are shown, reviewed, and a thorough assessment of the suggested strategy in comparison to current standards is presented. The paper's conclusion is presented in Section VI.

II. Related Works

Lu et al. [12] proposed utilizing a CNN to classify disease of plant leaf. They examined the most recent CNN networks that were relevant to classifying plant leaf diseases in their article. Additionally, they outlined the DL concepts involved in classifying plant diseases and provided the CNN methodologies used in the process. Additionally, it summarized various issues with the DL utilized for classifying plant diseases based on extrinsic and intrinsic characteristics, as well as the accompanying remedies. Inadequate datasets in terms of number and variety are the main issue with CNN-based DL's application to the categorization of plant diseases. This condition contributes to some extent to all the other issues that have been raised. The practical application is significantly influenced by adequate datasets. However, external factors like seasonality and climate may readily alter data collection, and image labelling is often a time-consuming and hard operation. These elements make it very challenging to create an effective dataset.

Sen et al. [13] proposed classifying leaf disease using the EfficientNet network. Considering the reality that the raw image size had to be restricted due to hardware constraints, the EfficientNet architecture provided superior outcomes than previous CNN algorithms that had been fed images as inputs with higher dimensions. When the initialization times of each model per session were looked at, AlexNet showed less overall accuracy and precision than the other models. It took 310 and 352 s in both the initial and augmented datasets, respectively. The dataset on plant leaf disease can be expanded, though. This will aid in the creation of models that can anticipate outcomes more accurately under challenging circumstances. Pathologists for plants and producers are going to be able to promptly identify diseases of plants and implement necessary precautions by utilizing these enhanced techniques in mobile situations.

Hassan et al. [14] suggested the use of transfer-learning and neural algorithms, researchers improved the identification of plant-leaf illnesses. They switched from standard suppression to depth-separable inversion in this study, which minimizes the amount of work of the computations. The models were trained on a dataset comprising 14 distinct species of plants, 38 different types of diseases, and healthy foliage from plants. Other parameters, such as the overall amount of sections, being abandoned, and the quantity of epochs, were used to evaluate the models' effectiveness. The created models fared better in terms of overall accuracy rates for sickness categorization than traditional handmade based on features methods. In comparison to earlier deep learning techniques models, the newly constructed model behaved more effectively while requiring less training time. The CNN-based deep learning techniques architecture has certain limitations even though it has excellent detection rates for identifying plant diseases. The disadvantages of them are that whenever there doesn't seem sufficient noise in the collection of photographs, the deep-learning model may be misclassified.

Zhou et al. [15] KNN Classifier is proposed for the proposed Color and Material Based Methodology for the Identification and Diagnosing the Leaf Disease. In the current study, the K-nearest neighbor classifier was recommended as a method for classifying and identifying leaf diseases. For categorization, the leaf disease images textural characteristics are retrieved. In this study, a KNN classifier will be used to categorize numerous plant species' illnesses. The suggested method has a 96.76% accuracy rate for correctly identifying and diagnosing the chosen illnesses. However, there are disadvantages and difficulties, including high computing costs, sluggish performance, memory and storage problems for huge datasets, sensitivity to metric selection and distance, and vulnerability to the plague of dimensionality.

Sibiya et al. [16] advocated the use of CNN in order to distinguish healthy leaves from leaves with illnesses on maize. To create a collection of networks for illness image recognition and classification, this study uses CNN aided principles. The CNN network was trained using Neuroph to identify and categorize images of the wheat diseases of the leaves that were gathered using a mobile device's camera and exercise. Three different forms of wheat leaf diseases could be distinguished by the created model from healthy leaves. This study focused on the ailments that cause the most harm to Southern Africa's maize crops, widespread rust and grey leaf spot. The calculation length and sensitivity to outliers of the procedure are both rather high.

Lv et al. [17] recommended using Feature Enrichment Based Maize Leaf Disease Detection and DMS-Robust Alexnet. They initially developed an architecture for leaf maize characteristic augmentation in order to improve the qualities of wheat in a complicated environment. Then, a special neural network called DMS-Robust Alexnet is developed. It is based on the core Alexnet architecture. The DMS-Robust Alexnet uses dilatation of conjunction and multiple scales conjunction to boost the effectiveness of feature extraction. proposed using DMS-Robust Alexnet and Feature Enhancement Based Wheat Leaf Disease Diagnosis. They initially built an infrastructure for leafy wheat characteristic augmentation to increase the attributes of wheat in a complicated environment. This DMS-Robust Alexnet, a one-of-a-kind neural network, is then developed. It is based on Alexnet's core framework. The DMS-Robust Alexnet improves feature extraction efficiency by utilizing multi-scale merging and synthesis dilation.

The literature review points out several shortcomings in the current methods of plant leaf disease classification, including the inability and difficulty of gathering sufficient data, hardware limitations, high computing costs, sensitivity of metric selection, and vulnerability to dimensionality constraints. These limitations make it more difficult to identify plant diseases accurately and effectively. The proposed solution uses an advanced hybrid ABOCNN deep learning strategy to tackle these problems. This method enables accurate disease diagnosis by dynamically focusing on relevant portions of leaf pictures using one-class neural networks and attention techniques. This strategy not only outperforms CNN-based and conventional methods in terms of operation, but it also enhances interpretability through attention maps, making it a viable substitute for improved agricultural outcomes. Feature Enrichment Based Maize Leaf Disease Identification with DMS-Robust Alexnet, CNN-based models, KNN Classifier, transfer learning, and Efficient Net are some of the approaches that have been assessed.

III. PROBLEM STATEMENT

The literature review, which emphasizes the major impact of diseases of plant leaves on agriculture and food security, serves as the foundation for the current study [18]. It is obvious that existing plant disease detection methodologies may not be able to deliver the level of accuracy and repeatability required for effective preventive and remedial interventions. This conclusion underscores the critical requirement for advances in plant disease detection systems, stimulating the development and research of a more precise and reliable techniques for dealing with the challenges these agricultural threats provide. The work intends to solve the identified challenges in plant disease diagnosis by developing a more complicated hybrid deep learning architecture and using a dependable strategy. The research aims to improve the capacity and understanding of the disease detection process while acknowledging the limitations of traditional approaches and CNN-based techniques in terms of consistency and accuracy. The goal is to increase disease detection efficacy by deleting unnecessary information and dynamically concentrating on disease-specific regions in plant leaf images utilizing one-class neural networks as well as attention procedures. This method attempts to advance disease detection approaches, resulting in more accurate and reliable outcomes in the natural setting of plant pathology [19].

IV. PROPOSED ADVANCED HYBRID ABOCNN FRAMEWORK

The proposed methodology for revolutionizing plant disease detection in leaves, named the Hybrid ABOCNN Framework, comprises multiple stages and processes designed to enhance the accuracy and efficiency of identifying diseases in rice leaves. The dataset used consists of 5932 images of rice leaves with diseases like brown spot, bacterial blight, blast, and tungro, which were obtained from fields in western Odisha. These images underwent augmentation, increasing the number of images by six times. The pre-processing stage involves applying a Gaussian filter to remove noise and blur, followed by feature extraction using the CNN approach. The CNN is a complex network consisting of inversion, pooling, and fully connected layers, which are trained using the VGG-16 structure. The incorporation of the Attention Mechanism enhances the CNN's performance by assigning weights to important spatial features, thereby improving disease detection and classification accuracy. The proposed Attention-CNN model combines the benefits of both CNN and the Attention Mechanism. Training is performed using the Adam optimization method with cross-entropy as the loss function. The overall methodology, from data collection and pre-processing to feature extraction and classification, aims to create a robust and accurate framework for identifying plant diseases in rice leaves, ultimately contributing to more efficient agricultural practices. Fig. 1 shows the proposed ABOCNN framework.

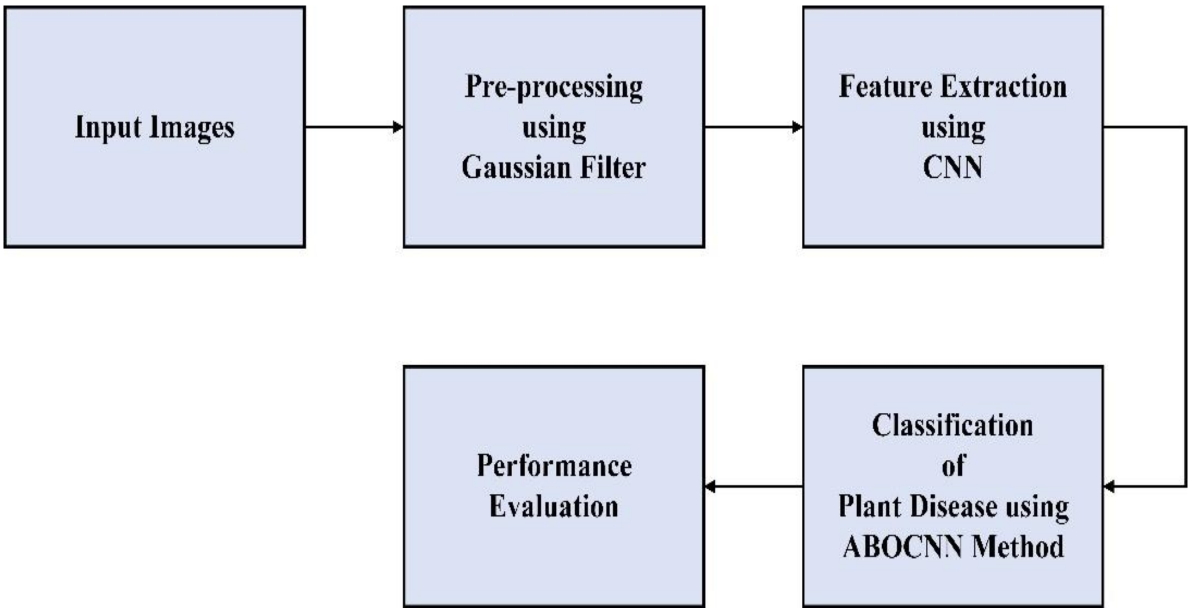

Fig. 1. Proposed hybrid ABOCNN framework.

A. Dataset

The collection comprises 5932 images of leaves of rice with diseases such as brown spot, bacterial blight blast, and tungro. The original images were taken using an exceptional grade of several fields of rice in western Odisha. The diseased areas in patches were obtained from the large original images. The patches were subsequently processed as samples of data after being converted to 300 300 pixels. Out of the 800 total images in the initial collection, 200 images from every group were picked for testing. The remaining 5132 images were augmented using the collection. Simple rotation and flipping operations were conducted to all photographs as part of the augmentation process, including revolve left 90 degrees, revolve right 90 degrees, flip vertically, flip horizontally and rotate 180 degrees. Consequently, including the upgraded images, the overall amount of images increased by six times. The more improved photographs there are, the more likely it will be that the camera system will pick up the proper qualities. Table I contains a list of the experiment's images by name and number. The data sample are allocated at randomly in amounts of 80:20 for both validation and training. Evaluation along with training samples are randomly selected for each execution [20].

TABLE I. TRAINING AND VALIDATION OF THE DATA SAMPLES

Leaf disease	Number of images used of augmentation	Number of original images	Number of images used for Training and validation	Number of images used for Testing
Bacterial Blight	1384	1584	8304	200
Tungro	1108	1308	6648	200
Brown Blast	1400	1600	8400	200
Blast	1240	1440	7440	200
Total	5132	5932	30,792	800

B. Pre-processing using Gaussian Filter

The process of separating features necessitates the transformation of unorganized information into quantitative qualities in order to capture and keep the specifics of the very beginning of data. Each patient processes information in a different way, and these traits are determined from the entire set of representations that were collected. To identify, the number of dimensions associated with the representation must be reduced, whereas the overall size of the representation increases throughout testing. In order to remedy this problem, features are removed. The GLCM is utilized during the feature extraction procedure. By producing several sets of images with specific values, it shows the graphical representation's structure of hierarchy. The GLCM displays the intensity of the displayed pixels by using the appropriate grayscale. The quantity of energy, comparison, connection, entropy, homogeneity, and other properties of the second-degree representation are evaluated in order to eliminate the statistically significant texturing feature. The first stage is image pre-processing. A Gaussian filter with a smoothed method is applied to the leaf during the pre-processing stage to minimize noise and eliminate blur from the image to increase the enhancement of the leaf image. The representation of this filter is defined in Eq. (1),

$$G(u,v) = \frac{1}{2\pi}(\varphi^2)\left(e^{-\left(\frac{u^2+v^2}{2e^2}\right)}\right) \quad (1)$$

Intensity gradient of the image is found out as given below in Eq. (2)

$$N(v,v) = \sqrt{g_u^2(u,v) +}\, g_v^2(u,v) \quad (2)$$

Edge thinning occurs when the gradient's degree is determined based on the strength of the edges. To eliminate the visible edge pixels caused by noise in the image, edge pixels with inadequate gradient values are deleted, while those with large gradient values are retained. a technique for computing texture and color information simultaneously. The texture of leaf images is often inconsistent, making it difficult to recognize textural patterns. Furthermore, typical techniques lose chromatic information, preventing them from supplying the key texture feature. In this study, we offer a novel technique in which the input image is completely enclosed by a circular window that travels over it [21].

The coordinates of the point (x, y) is home to the shade vector of characteristics (u, v). The supplied dimensions for (u, v) are (q cos t, q sin t), where u is equal to q cos θ and v is equal to q sin θ. The location of the starting point of these orientations is the circular window's centroid. The t(r) represents the color-texture translation of the provided two-dimensional images D (u, v) at r radius. This may be calculated through calculating the mean of D (q cos θ, q sin θ) within a particular region of r. It is expressing itself as Eq. (3):

$$t(r) = \frac{1}{2\pi r}\int_0^{2\pi} D(qcos\theta, qsin\theta)d\theta \quad (3)$$

C. Feature Extraction Using CNN

CNN are an appropriate strategic option for feature extraction in such circumstances because of their exceptional ability to extract discriminative and hierarchical characteristics from images. CNNs are appropriate for extracting disease-specific properties from plant leaf images because they are exceptionally effective at automatically learning and identifying complicated patterns. CNNs are advantageous because they are capable of transforming raw pixels into significant characteristics by reducing the dimensionality of images while maintaining essential information. It leads to more accurate and dependable identification of diseases by expediting the following process of categorization and improving the model's capacity to recognize small modifications and disease-related patterns. CNNs are a significant tool in the field of agricultural disease diagnostics because of their well-known versatility and scalability, which allow them to handle a wide range of plant species and diseases.

CNN are complex networks, and how effectively the network functions depend on how it is built. Its three component parts are the inversion layer, pooled layer, and the fully associated layer. While the initial two layers together constitute the extractor of features, the last layer acts as classifiers. The subsequent layer of pooling reduces the geographic extent of the properties that the previous layer of inversion recovered. The layer with all connections, followed by softmax, classifies the images using the feature that was extracted. The converging part of the method takes the raw image and extracts its properties using a set of adaptable filters. By doing a window that slides between the dot based on every filter and the original image pixel, a 2-D map of features is created. The total area of the feature map is decreased via a subsampling layer termed max pooling. The layer of data that is entirely interlinked is then used to link the developed feature map to each of it completely. Softmax constructs a multiclass problem and gives every category a decimal probability in order to categorize the images.

The VGG-16 structure is a large convolutional network with parameters that have previously been taught on the over three million clearly annotated images in the ImageNet Database. To acquire the categorizations, this data set is utilized to train and improve the earlier trained VGG-16 model [22]. After synchronizing the attributes from the source images, each image's input pixel is increased by the relevant characteristic pixels in the convolutional layer. Divide the outcome by the total amount of pixel in the characteristic after adding all the pixel values. The calculated values have been added to reflect the feature map, causing the enhancement to be utilized on the total image. Each calculated value occupies a space on the characteristic map. As a result, all of the characteristics are processed and multiple characteristic maps are created. The Eq. (4) to obtain the convolutional layer is the following,

$$v_{lmn} = \sum_{B=0}^{B-1}\sum_{C=0}^{C-1}\sum_{f=0}^{C-1} s_{l+c,m+f,K^c cfbn}^{(l-1)} + f_{imn} \quad (4)$$

where, f_{imn} is generally set to which is not contingent on the image's component position. $K^c cfbn$ as an identical value of weight. After repeatedly applying the layers of convolution to the input images, a collection of feature maps may be obtained. Let D_i represent the characteristic map of the i^{th} layer in CNN, then the D_i can be generated as in Eq. (5)

$$D_i = \rho(D_{i-1}V_i + k_i) \quad (5)$$

where, D_i is the characteristic mappings of the presently active layer of networks and D_{i-1} is the convolution characteristic of the preceding layer. The rectification functional is represented by ρ (·), the i-th layered offsets matrix is called k_i, and the layer's weighting is called V_i. The purpose of layered pooling is to decrease the overall quantity of distance, which can lower the processing expense and consequently lower the risk of excessive fitting. During (6), at the k-th layer of pooling, a corresponding distinct on the ith isolated reactive fields is found.

$$v_i^k = down(v_i^{k-1}, r) \tag{6}$$

where, down $(\cdot)$ demonstrates the actions for down-sampling, v_i^{k-1} is the characteristic vectors in the preceding layer, and r is the pooling size. The Softmax function is represented in Eq. (7)

where, r is the pooled dimensions, v_i^{k-1} is the characteristic vectors from the preceding layer, and down $(\cdot)$ is the down-sampling value. Multiple fully connected (FC) layers can occur after a combination of pooling and convolutional layers. These layers utilize the gathered characteristics to categorize images. The Soft max operates is commonly utilized for category predictions using the features obtained from the previous layers. Eq. (7) represents the Softmax function.

$$Softmax(k) = e^{ij} \setminus \sum_{l=1}^{l} e^{il} for(j = 1, \dots \dots . l) \tag{7}$$

where, K represents the dimension of the z vector [23].

D. Attention Mechanism Integration

The main goal of the suggested method is to improve CNN's performance by employing the Attention Mechanism to assign importance and selectively focus on aspects in images that are important concentrate situation. The main benefit of the Attention Mechanism is that it can dynamically assign weight to different spatial properties in characteristic maps, which helps the model make better decisions. Through this technique, the Attention-CNN model develops flexibility in collecting complex information and adapting to varied datasets, which eventually leads to greater illness detection. It also improves classification accuracy. An essential part of the suggested deep learning approach for the precise recognition and identification of plant leaf diseases is the Attention Mechanism, which is crucial in improving the model's accuracy and interpretability.

By keeping the context-relevant properties, the CNN is enhanced by the attention model. Each block's characteristics are combined with those from the layer above it in the prior based model. In this manner, all characteristics gathered from the prior CNN blocks are given equal weight. Important features from the preceding blocks must be weighted highly in relation to other features in order to learn accurate feature values. As a result, a mechanism for attention was added to the CNN architecture to enable learning and selection of standout characteristics from earlier blocks. This model generates an attention mask that equalizes the relative importance of spatial characteristics at that feature map. Using a method for paying attention between blocks, the CNN framework learns the weighted utility for simulating the responses from the prior blocks. The relationships from the previous blocks which were skipped had been graded across the dimension axis for all pixels in that layer's spatial range [24].

The outcome of the convolutional layers 'x' in both the initial and subsequent blocks is directed through two functional channels, H(x) and I'(x). H(x) represents the set information procedures that were used to take 'x' and feed it forward in a straightforward feed-forward fashion to the following block. I'(x) denotes the collection of procedures that skip 'x' across convolutional and maximum-pooling layers and are weighted with attention. The output U(x) from a CNN block is produced using the weighted summation is represented in Eq. (8)

$$U(X) = H(X) + I'(X) \tag{8}$$

The functional path I'(x) is computed as in Eq. (9)

$$I'(X) = I'(X) * \varphi \tag{9}$$

where, 'φ' is a matrix containing attention weights with dimensions that match those of I(x)'s dimension in space. The attention weight matrix 'φ' ' is point-wise amplified over the relevant cross-section of I(x) and disseminated along the entire depth. By incorporating a mechanism for attention into CNN, the network may use the input from the present instant and the output from the previous moment to adaptively distribute the weighting for the data of the whole network. To increase the classification's accuracy and flexibility, significant details of the image might be concentrated on. Based on this, the CNN's attention concept is added to form the Attention-CNN model. Every inversion layer of the four stages that make up a single layer of convolution is followed by a layer of attention in order to successfully accomplish the weight transportation. The convolution kernels for each layer are 8x3x3, 16x 5, 32x 3, and 32x 3, respectively. The initial and final convolution layers are joined by a pooling layer. The maximum amount of nodes in the full interconnections layer is set to 64, and the output of the layer that performs convolution is used as the layer's input. The resultant layer categorizes the particles into four groups, and there are four output layer nodes. The attention-CNN model consists of the inputs, convolution, attention layer, output layers and fully connected layers. The input layer is made up of four nodes, or the designated images of four distinct types of particles, as the data being input is a pictorial representation of four different particle types.

The network's output no longer looks linear, which increases a network's flexibility and allows it to fit a wider range of curves. The Attention-CNN model uses two activating parameters, Relu and softmax, for its hidden and output components, respectively. Relu can deal with elevation variation throughout the information transfer process. Finding the gradient is straightforward and may significantly increase the gradient's downward convergence rate. Expression of Relu function is represented in Eq. (10)

$$ReLu = max(0, y) \tag{10}$$

where, $\omega(z) - y$ is the error between the outcome and the provided value [25]. Fig. 2 represents the Principle of attention Mechanism.

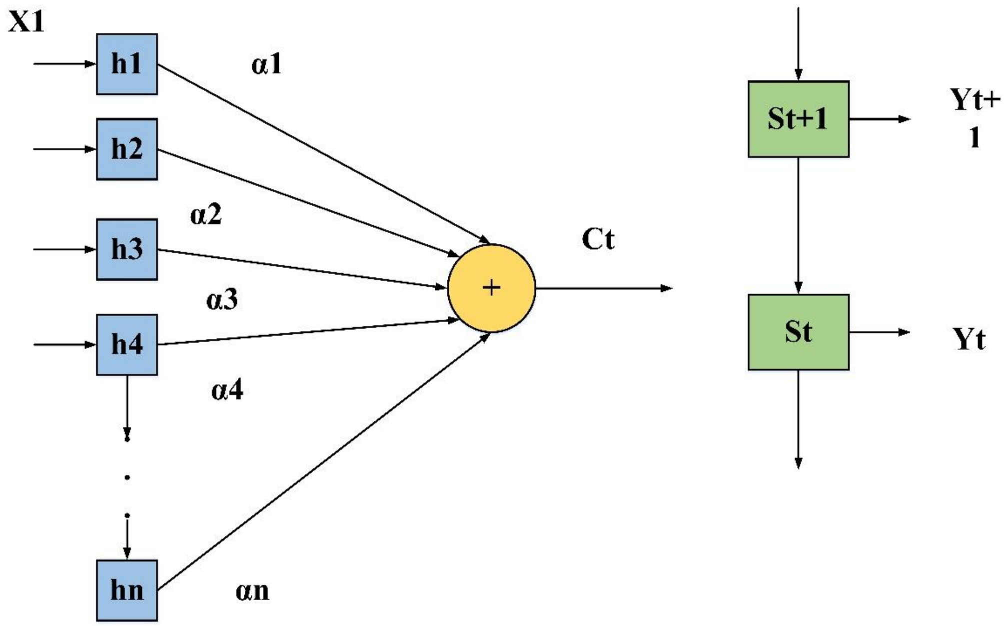

Fig. 2. The principle of attention mechanism.

Softmax achieves various classifications by mapping the output of many neurons to the coordinates (0, 1). i represents the ith component of an input array, assuming one exists; the value of softmax component is computed by Eq. (11)

$$K_i = \frac{f^i}{\sum_{j=1}^{n} f^i} \tag{11}$$

where, n indicates all input elements. Because the momentum element is incorporated into the updating process and the Adam optimization method fully use both the gradient's means. The calculation process of Adam is represented in Eq. (12) to Eq. (16):

$$v_t = \gamma_1 \delta_{t-1} + (1-\gamma_1) k_t \tag{12}$$

$$m_t = \gamma_2 \delta_{t-1} + (1-\gamma_2) k_t^2 \tag{13}$$

$$\hat{v}_t = \frac{v_t}{1-\gamma_1^t} \tag{14}$$

$$\widehat{m}_t = \frac{m_t}{1-\delta_1^t} \tag{15}$$

$$k_{t+1} = k_t - \frac{\partial}{\sqrt{\widehat{m}_t} + \varepsilon} \hat{v}_t \tag{16}$$

where, v_t is estimate of first-order moment, m_t is momentum term of second-order, γ_2, γ_1 are values of the dynamic, k_t is the gradients of the expense value after t times, $\hat{v}_t$ is first moment correction variable, $\widehat{m}_t$ is second moment correction variable of, k_t is the variables of the t iteration method, and ε is a small number that can avoid the zero denominator. In order to measure the discrepancy among the expected outcome and the actual value during neural network training, the loss function is utilized. This function also serves as a benchmark for testing the model's performance. Cross-entropy cost function, which may be represented in Eq. (17) as the loss function for Attention-CNN,

$$H = -\frac{1}{n} \sum_u u_j (\rho(x) - y) \tag{17}$$

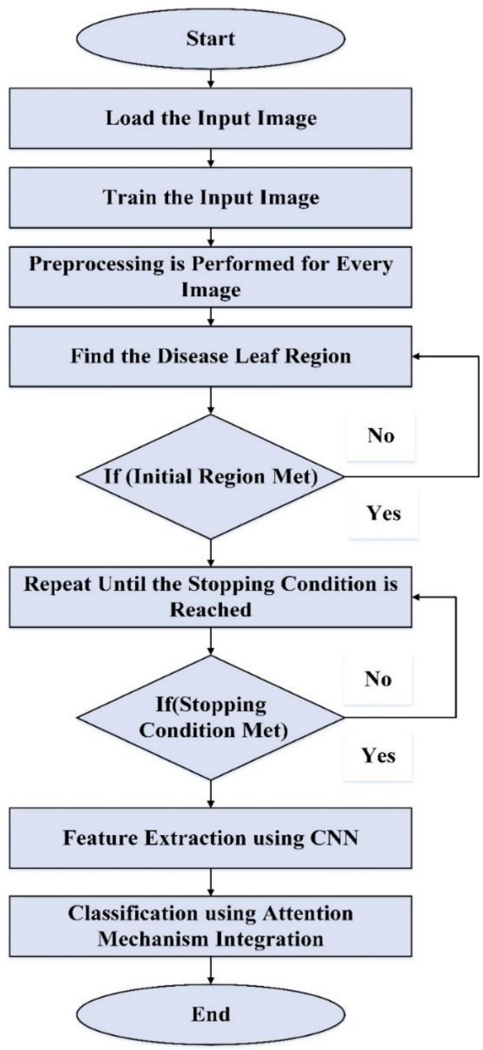

Fig. 3. Flow chart of the proposed system.

where, u is the resultant significance, y is the actual quantity, n is the total of the specimens, and u is the measurement value. In Eq. (18), the changing value of μ is computed as follows:

$$\frac{\partial y}{\partial x} = \frac{1}{n}\sum_{u} u_j(\omega(z) - y) \tag{18}$$

Fig. 3 illustrates the suggested flow diagram for detecting leaf disease. The information is initially loaded. The images were pre-processed with a Gaussian filter to eliminate the noise. The characteristics are then retrieved using the CNN approach, and the suggested classifier is used to classify the leaf illness.

V. RESULTS AND DISCUSSION

The suggested approach has been tested with leaf samples and run in the MATLAB program on the Windows 10 operating system. [26] employed a 3D CNN model for the classification of charcoal rot illness because to its excellent classification accuracy and capacity for automatically acquiring the spatio-temporal characteristics without handcrafting [27]. The findings showed that the model worked well on both training and test information. However, it was found that when the batch's total value grew, the steady-state condition in the experiment's data was delayed. The model's performance, which was previously subpar on such a short dataset, has been considerably enhanced using VGGNet. We obtained a threshold after which the precision continued to decline and the amount of loss was not lowering on the validation and training data. The successful classification of a training set increases over time and becomes stable over time. At the beginning of the cycle, the test samples' classification accuracy improves significantly. After the early oscillations, the test sample's precision approximate that of the first training specimens and as the number of trials increases, it practically remains constant [28]. The integration of revolutionary ABO-CNN is employed to identify a leaf disease. Performance indicators like Precision, Accuracy, F-measure and Recall, are used to evaluate the effectiveness of the proposed method.

A. Accuracy

The overall accuracy of the approach indicates how well it works in all classes. In general terms, accuracy is the notion that all circumstances can be predicted with precision. Eq. (19) represents accuracy.

$$A = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \tag{19}$$

B. Precision

Precision is determined by counting the precise favorable evaluations that deviate from the overall positive ratings. The portion of accurately recognizing the affected area is calculated using Eq. (20).

$$P = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{20}$$

C. Recall

The recall measures the relationship among the total number of correctly identified positive specimens and the actual positive results. The proportion of forecasts that properly detected the leaf disease indicated by Eq. (21),

$$R = \frac{T_{pos}}{T_{pos}+F_{neg}} \tag{21}$$

D. F1-Score

The F1-Score is computed by combining recall and precision; this results in the F1-Score shown in Eq. (22).

$$F = \frac{2\times Precision \times recall}{Precision \times recall} \tag{22}$$

E. AUC and ROC

AUC is an acronym for Area under the ROC Curve, which is a prominent assessment measure for binary categorization tasks in machine and deep learning. The AOC evaluates the area under the ROC (Receiver Operating Characteristic) curve, which is a visual depiction of the effectiveness of a binary classification algorithm. In a binary categorized issue, the classifier attempts to determine whether the input data relates to a negative or positive category. For various categorization criteria, the ROC curve displays the T_{Pos} vs the F_{Pos}. The AOC has a value between 0 and 1, with greater numbers signifying increased efficiency. The ideal classifier has an AOC of one, whereas a totally random classifier has an AOC of 0.5. Because the algorithm takes into consideration all potential levels of classification and offers a single value to evaluate the effectiveness of various classifiers.

F. Miss Rate

The miss rate is a measure of the systems or model's sensitivity or ability to correctly identify and classify diseased plants. A lower miss rate indicates a higher level of accuracy and performance in detecting and classifying plant diseases, as it means fewer diseased plants are being missed or misclassified.

According to Table II, the CNN's accuracy in the training and testing phases was 99.4% and 97.5%, respectively. The testing and training procedures accuracy rises to 99.6 and 99.4, accordingly, when ABO-CNN is used. A review of performance is displayed in Fig. 4.

Table III and Fig. 5 show a comparative analysis of several categorization approaches for the identification of plant leaf diseases, as well as an overview of their corresponding performance indicators. The CNN model performs well overall, with an accuracy of 86.8% with high precision (96.9%), recall (98.5%), and F1-Score (97%). With a lower recall of 95% and a higher accuracy of 97.9%, the Deep Convolutional Neural Network (DCNN) model produces an F1-Score of 96%, suggesting that it exhibits less robust disease identification. While the accuracy of the KNN (K-Nearest Neighbors) model is 98.2%, its precision (89.5%), recall (89.1%), and F1-Score (89%) are lower, indicating that it may have some limits when compared to accurately detecting disease cases. The Proposed ABO-CNN approach, on the other hand, performs better than all the other models. Its exceptional accuracy of 99.6%, combined with high precision (99.4%), recall (99%), and an exceptional F1-Score of 99%, demonstrate its outstanding capacity to reliably and accurately detect plant leaf diseases.

TABLE II. PERFORMANCE EVALUATION

	CNN	ABO-CNN
Training	98.1	99.9
Testing	97.5	99.4

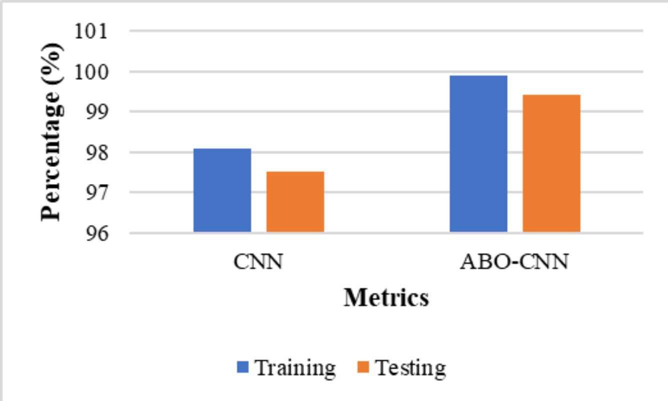

Fig. 4. Accuracy comparison for existing and proposed method.

TABLE III. COMPARISON OF ACCURACY, PRECISION AND RECALL

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
CNN [14]	86.8	96.9	98.5	97
DCNN [12]	97.9	97.9	95	96
KNN [15]	98.2	89.5	89.1	89
Proposed ABO-CNN	99.6	99.4	99	99

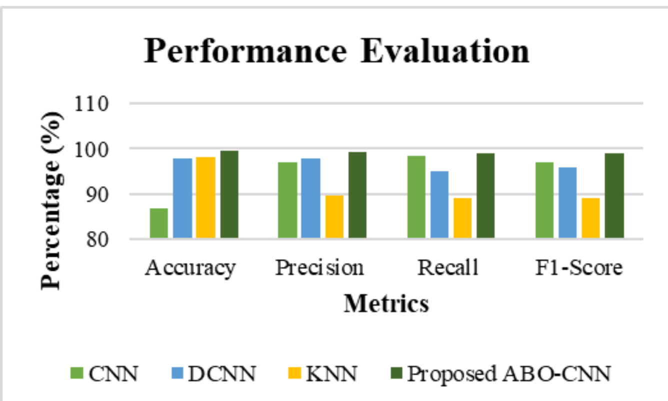

Fig. 5. Performance comparison of proposed and existing techniques.

TABLE IV. EFFECTIVENESS ASSESSMENTS OF THE METHODS BASED ON AUC-ROC

Methods	AUC-ROC
Random Forest [29]	0.922
SVM [29]	0.886
VGG-19 [30]	0.991
ResNet50 [30]	0.847
Proposed ABO-CNN	0.987

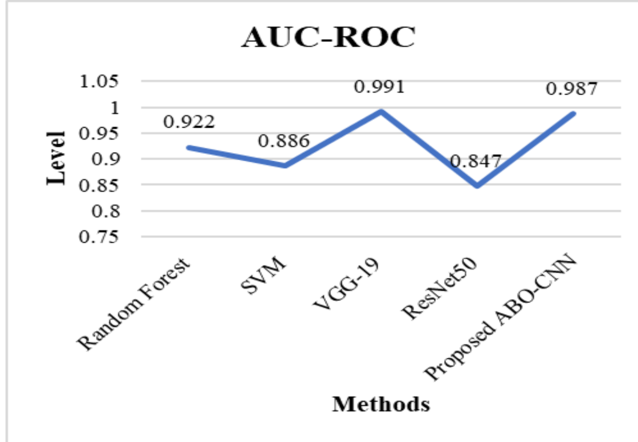

Fig. 6. Comparison of AUC-ROC curves of proposed and existing techniques.

Table IV and Fig. 6 gives the performance assessments of the methods based on AUC-ROC Curves. According to the test findings, the AUC-ROC scores of the Proposed ABO-CNN are greater than those of all other current models, and the performances of Random Forest and VGG-19 classifiers stand out, with AUC-ROC values extremely close to 1.

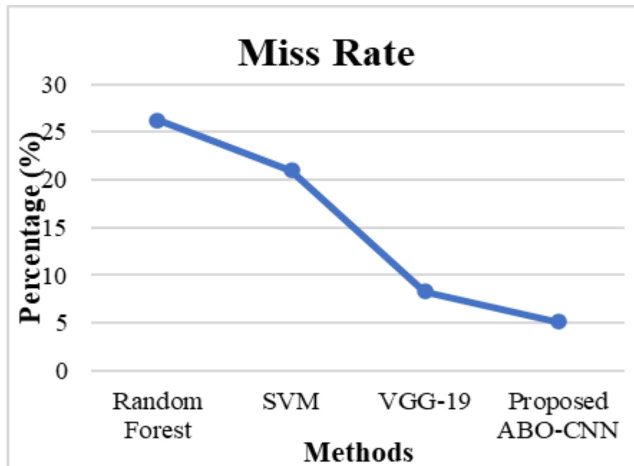

Fig. 7. Comparison of misclassification rate of proposed and existing techniques.

Fig. 7 shows the Comparison of Miss rate of the proposed method and existing methods. It shows the miss rate of the proposed method is lower than that of the existing methods [31].

G. Training and Testing Accuracy

Fig. 8 represents that by combining attention mechanisms and one-class neural networks, our novel architecture significantly enhances the accuracy of both testing and training phases. The attention mechanisms dynamically focus on disease-specific regions within leaf images, effectively capturing crucial features while eliminating irrelevant information.

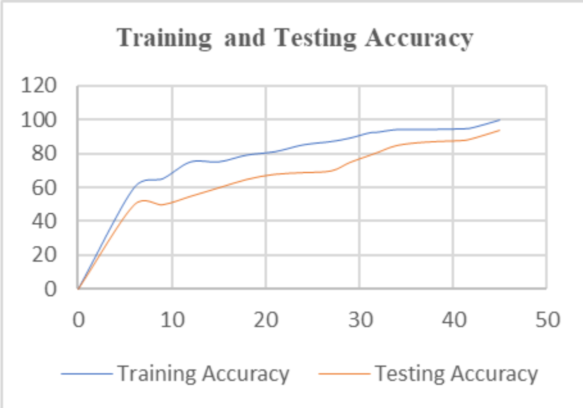

Fig. 8. Training and testing accuracy.

Simultaneously, the one-class neural network is trained on healthy leaf samples, enabling it to detect anomalies corresponding to diseased instances. As a result of this hybrid approach, our framework achieves exceptional accuracy rates of 99.6% during both training and testing, surpassing conventional methods and fully CNN-based techniques.

H. Training and Testing Loss

Fig. 9 represents that during the testing and training phases, the proposed framework exhibits remarkable performance in minimizing loss. Through the integration of attention mechanisms and one-class neural networks, the architecture effectively captures disease-specific features within leaf images while filtering out extraneous details. The attention mechanisms dynamically focus on relevant regions, aiding in accurate feature extraction. Simultaneously, the one-class neural network learns to recognize healthy leaf patterns and detects anomalies that indicate diseased instances. As a result, our hybrid ABOCNN framework demonstrates outstanding performance in minimizing training and testing loss, indicative of its ability to learn and generalize disease characteristics.

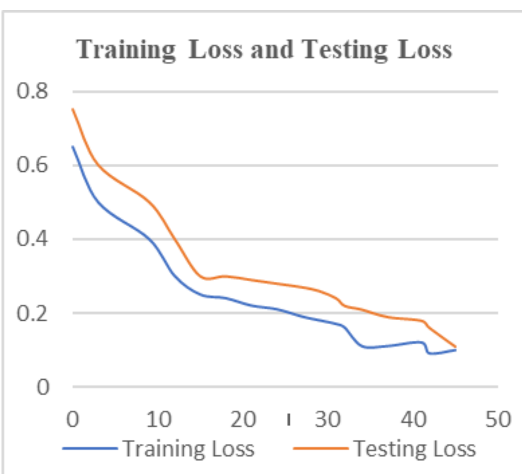

Fig. 9. Training and testing loss.

I. Discussion

The research approach was chosen based on the study's objective of revolutionizing plant disease detection in leaves, aiming for advanced and accurate identification. The chosen methodology of a Hybrid ABOCNN Framework was selected for its ability to integrate deep learning and attention mechanisms, which are effective in identifying disease-specific features while ignoring irrelevant information. The choice of dataset, which comprised 5932 images of rice leaves with various diseases, was motivated by the need for a comprehensive dataset to train and test the proposed framework. The dataset was augmented to increase the variety and quantity of images, enhancing the framework's ability to learn and generalize disease characteristics. The research could have been undertaken using other approaches, such as traditional machine learning algorithms like K-Nearest Neighbors (KNN) or Support Vector Machines (SVM). However, these methods may not be as effective in capturing complex patterns and hierarchical features present in images, making them less suitable for plant disease detection tasks. The proposed methodology was benchmarked against other methods, such as the CNN model, Deep Convolutional Neural Network (DCNN), and KNN, demonstrating superior accuracy and performance in detecting plant leaf diseases. The strengths of the research approach lie in its innovative integration of deep learning and attention mechanisms, leading to an accurate and efficient framework for plant disease detection. Overall, the research approach has successfully achieved its aims and objectives, providing a powerful tool for revolutionizing plant disease detection in leaves.

VI. Conclusion and Future works

Finally, effective agricultural administration and food security are dependent on early and precise detection of plant leaf diseases. This study presents a novel deep learning technique for the exact detection of numerous plant diseases, which employs an upgraded hybrid ABOCNN architecture. By combining processing of attention with one-class neural networks, the proposed approach extracts disease-specific properties from leaf images with an outstanding 99.6% accuracy. This is a significant advancement in the identification of plant diseases, exceeding traditional approaches and CNN-based algorithms. Integrating attention maps not only improves diseases detection accuracy but also generates the model more explainable by offering insight into how it makes choices. It is critical for one to understand that the required computer resources may preclude this method from being used in circumstances when resources are limited. To address resource constraints, future research should focus on improving the Combination Hybrid ABOCNN System to enable real-time plant disease detection in field settings. This might entail deploying embedded or mobile technologies. Furthermore, expanding the dataset to include a broader range of plant species and illnesses will improve the model's performance and adaptability to various agricultural circumstances. These advancements have the possibility to significantly improve agricultural outcomes by developing more robust and adaptable systems for disease detection. The concerns regarding the small dataset and the potential for overfitting are duly noted. To address these issues, a larger dataset could be employed for more comprehensive training and testing, thereby providing a more robust performance evaluation. Additional experiments could be conducted with varying dataset sizes to assess the impact on accuracy and generalization capabilities. Moreover, techniques like cross-validation could be employed to ensure that the model's performance is consistent across different subsets of the data. These steps would provide a more thorough analysis of the proposed methodology and help ensure that the achieved high accuracy is not merely a result of overfitting.

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