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A Novel Chimpanzee-Based Swin Transformer Model for Detection of Rice Disease with Mapping System in Drone-Based Agriculture

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Abstract: Rice is needed daily. This food contains carbs, which the body requires for energy and growth. Economically beneficial rice. Infected rice plants waste field crop and reduce yield if not monitored. Field monitoring is needed to detect rice plant illnesses. Recent agricultural surveillance uses drones with cameras and GPS. It's quick, independent data collection over a vast area. This study proposes a drone-based (IoT) building that detects and classifies rice diseases using real-time data and image processing to boost rice productivity. The method uses a GPS sensor to map ill rice plants in rice fields in real time. This study suggests using the COA to determine the optimal network hyperparameter values for autonomous rice image categorisation. The Swin-Transformer links non-overlapping windows from the previous layer by changing window partitions, thereby capturing multi-scale properties. The improved approach detects six categories, including healthy, leaf blast, and bacterial leaf blight. Experimental analysis used Accuracy, Precision, Recall, Specificity, and F1_score. For training 80% and testing 20% data, the Chimpanzee-based model obtained 96% accuracy, 99% specificity, 96.09% F1_score, 96.26% precision, and 96.14% recall, a 3% to 5% improvement over earlier techniques. The suggested enhancement enhanced literature findings compared to other methods using the same or similar datasets.

Keywords: Image Processing; GPS Sensor; Rice Plant Disease Classification; Internet of Things (IoT); Multi-Scale Features; Chimpanzee Optimisation Algorithm; Swin Transform; Chimpanzee Optimisation Algorithm (COA).

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1. Introduction

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Rice is a staple food essential to human survival [1]. It's an excellent source of the carbs necessary for healthy human growth. Farmers worldwide rely heavily on rice production, making it an essential crop for national economic growth [2]. However, several diseases afflict the rice plant due to climate and other environmental factors [3]. To detect the presence of these diseases at any stage of rice plant development, a system must be in place to regularly monitor the rice field. Insect infestations and plant diseases are two key reasons why food is becoming less accessible and less sanitary, according to the FAO [4]; [5]. Plant diseases vary with the seasons due to factors such as the pathogens present, the weather, and the crops planted [6]. Abiotic factors (drought, waterlogging, salt, etc.), biotic factors, and climatic change all contribute to environmental stress in crops [7]; [8]. Detection of rice diseases using a drone-based mapping system in agriculture can be an effective and efficient way to monitor and manage crop health [9]. Drones equipped with mapping systems, such as multispectral or hyperspectral sensors, can capture high-resolution images of rice fields and provide valuable data for disease detection [10]; [11]. Here's an overview of the process: drone flight and data collection, with a drone equipped with the mapping system flown over the rice fields, capturing images across various spectral bands. Multispectral sensors can capture data in specific wavelength ranges, while hyperspectral sensors provide even more detailed spectral information [12]; [13]. Image processing and analysis: the captured images are processed and analysed using specialised software [14]. This software can extract relevant information from images, such as vegetation indices and spectral signatures indicative of crop health [15]. By comparing extracted information with predefined disease signatures or healthy reference data, the software can identify areas of the crop exhibiting disease symptoms. Different diseases may exhibit distinct spectral patterns, allowing for accurate detection [16]; [17]. Drones equipped with mapping systems provide high-resolution data, enabling precise identification and mapping of disease-affected areas. This targeted approach helps optimise interventions and minimise resource waste. Cost-effective: Compared to traditional methods of disease detection, such as manual scouting or satellite imagery, drone-based agriculture offers a cost-effective solution [18].

Drones are relatively inexpensive, and their technology enables rapid data collection and analysis. In conclusion, drone-based agriculture with a mapping system proposes an efficient and effective means of detecting rice diseases [19]. It enables early detection, precision targeting, and informed decision-making, leading to improved crop management and reduced losses. In recent years, promising methods for detecting and localising illness have been proposed, employing autonomous monitoring and recognition systems. The identification and diagnosis of agricultural irregularities have received a fresh boost from developments in sensor technology and data processing [20]. Data collection from the ground, from sensors like RS or ground equipment, and from the development and testing of machine learning algorithms are all viable options for doing disease monitoring [21]. Smart algorithms implemented as part of management practises improve profitability, sustainability, and resource preservation. As a whole, it enables the timely, appropriate, and successful administration of therapy [22]. In addition, IoT sensors and remote sensing pictures may be used to measure environmental factors, plant canopy, and leaf indices for use in the agricultural sector [23]. To better understand crop growth circumstances and disease symptom development, a range of data extraction methodologies must be combined using data fusion techniques [24]. The use of machine learning-based data fusion for agricultural data has the potential to significantly improve plant defence, especially in disease detection and early disease diagnosis. As a result, several fusion approaches based on multi-sensor and sensing technologies have been applied in agriculture to support this drive [25]. Extensive study in the field of digital agriculture, chiefly for plant monitoring, management, and protection, has emerged from the utilisation of agricultural statistics from various acquisition technologies, as well as machine learning and fusion algorithms, resulting in a sizeable body of scholarly literature [26]. Several literature reviews on the application of machine learning strategies to agriculture have been published over the past decade, with much of the focus on Internet of Things (IoT) data, ground imagery, and remote sensing imagery [27].

Farmers can't possibly walk the whole length of their fields every day, and even if they could, they wouldn't have time to inspect each rice plant. Even if it were possible to have farmers check rice plants every day, doing so would be a time-consuming and expensive hassle that could potentially injure other rice plants [28]. Physically classifying or diagnosing a problem is difficult because it requires observing several factors, such as the situation and the environment. One of the newest developments being investigated by scientists is the application of different agricultural areas identify diseases in rice plants at an early stage [29]. Due to advancements in digital image processing and identification systems, it is now possible to identify sick crops and categorise the type of disease they have.

However, AI and ML on their own won't be adequate; some academics advise using drone technology and the IoT to create a comprehensive scheme that can appropriately support farmers in achieving good outcomes and reducing costs [30]. However, the most crucial part would be a state-of-the-art ML algorithm, method, or procedure for identifying and correctly diagnosing rice illness. Therefore, scientists are still looking for the best ML method for identifying plant diseases [31]. Recent studies have been conducted in this area, but experts are still seeking the best and most precise answer. Increased productivity and improved quality at lower costs are only two of the many evident motivations for developing a system to aid rice farmers in the initial diagnosis of rice disease. The primary focus of agricultural technology research is on improving yields and quality [34]. It has been argued that researchers should pay special attention to rice plants by focusing on the illnesses that affect them and on ways to prevent or detect them early [35]. Whether it's for the rice ounces people eat or any other agrarian commodity of equal or greater significance and popularity, research in this area is essential:

- To analyse the collected data using specialised software or collaborate with experts to interpret the results. Your involvement can ensure accurate and reliable data analysis.
- The primary objective of this study is to develop a system that automatically identifies, categorises, and diagnoses rice diseases without human interaction using innovative, optimised deep learning (DL) approaches.
- The ultimate goal is to propose new approaches that improve diagnostic accuracy relative to state-of-the-art procedures, using the same or comparable-sized datasets from the existing literature.
- By actively participating in detecting rice diseases using a drone-based mapping system, you can help enhance the system's accuracy, usability, and effectiveness, ultimately benefiting the farming community as a whole.

2. Related Works

Rice panicle neck explosion and rice stem blast are the four rice illnesses that Zhao et al. [32] advise and consider crucial. YoloX was initially used to identify affected rice areas, and the unique rice disease photos were then cropped to create a new dataset. The first-stage disease patches were utilised as input to a second-stage Siamese Network analysis. YoloX achieved the best detection performance in the comparative trial, with a mAP of 95.58% on rice disease photos. Siamese Network outperformed other models in the identification phase, achieving 99.03% accuracy. In conjunction with state-of-the-art tactics, the proposed RiceNet model performed better in experiments. In addition, it successfully identified rice illnesses at the fastest possible rate while maintaining the lightest possible weight. An enhanced DenseNet network (DenseNet) is the basis of a system for rice disease diagnosis proposed by Kundu et al. [33]. The DenseNet reference model is used here, and channel excitation is employed to boost positive features while dampening negative ones. Next, certain regular convolutions in the dense network are replaced with divisible convolutions to maximise parameter usage and accelerate training. The AdaBound algorithm, when used in conjunction with the adaptive optimisation technique, speeds up the tuning process. The experimental results across five different rice disease datasets show that the strategy described in this study achieves an average classification accuracy of 99.4%, an improvement of 13.8% over the baseline model. Various additional recognition techniques are also evaluated, including ResNet, VGG, and Vision Transformer. This approach offers higher recognition accuracy, effective classification of rice diseases, and a novel approach to crop development.

For automated identification and diagnosis, Mohapatra and Das [42] present an AlexNet model trained with transfer learning. Bacterial diseases are among the most prevalent affecting rice plants, and they can be difficult to distinguish by visual inspection alone. The data set may be downloaded for free from the 'Kaggle' website. For the task on the 'Kaggle' dataset, the projected AlexNet is perfect. To achieve accurate disease prediction in rice, Mehzabeen and Gayathri [43] propose a smart segmentation and classification approach. This method rolls feature extraction/selection and classification into a single step. First, preprocessing using the Synthetic Minority Oversampling Technique normalises the data. Second, an effective segmentation method based on modified feature-weighted fuzzy clustering is applied. After that, Principal Component Analysis is used for Feature Extraction to improve the classifier's accuracy. Feature selection is performed using Linear Discriminant Analysis. Finally, to boost prediction performance, a hybrid classification model combining an SVM is used. Metrics, timeliness, and F-measure are used to evaluate the results. In all, the study considered 3416 images of the four most common rice leaf diseases: bacterial blight, blast, brown spot, and tungro. Here, first perform four separate experiments: among the detection methods, DenseNet121 was found to be the most effective, with an accuracy of 93.87%. Second, three trained using the deep features outperform other deep features and machine learning methods. In addition, (DMD), an attention-driven pre-processing mechanism, is investigated to help locate the source of the infection.

The sparse component of the DMD method is utilised to generate a hard attention map, which is multiplied by the input images to produce maps in rice leaf disease detection. Ten Deep Convolutional Neural Network (DCNN) models were evaluated using both the raw pictures and DMD-preprocessed versions. Compared to other models, the XceptionNet deep feature with an SVM classifier achieves 100% test accuracy on images preprocessed with DMD. Finally, photographs taken in the rice field are evaluated to see how well the suggested DMD-based attention-driven pre-processing worked. The XceptionNet model achieves a higher classification accuracy (94.33%) than competing transfer-learned models. For disease detection in the big three cereals (corn, rice, and wheat), Pang et al. [36] propose a single lightweight CNN model. To reliably detect illnesses with varying infected areas, the suggested model employs convolutional layers of varying sizes at the same level. The experimental results show that the proposed model achieves 84.4% accuracy with only 387,340 parameters, outperforming models such as VGG16, VGG19, ResNet50, ResNet152, MobileNetV2, Corn, Rice, and Wheat, respectively, validating its usefulness as a multi-functional tool. The suggested model's superior performance and lightweight nature make it a practical option for disease diagnosis, even in resource-limited settings. To restore the accuracy of disease detection in rice plants, Agarwal et al. [37] developed a lightweight model. To accomplish the aforementioned goal, it developed a CNN model, "LW17," to identify rice plant illness more accurately than several pre-trained models, including VGG19 and DenseNet201.

The method used the suggested technique on UCI's illness detection datasets and experimented with various configurations of model layers, training-test splits, learning rates, and epochs. Compared to previous models, this model reduced complexity and processing costs. Using max pooling with the "Adam" optimiser and a learning rate of 0.001, the LW17 model achieved a best-case accuracy of 93.75%. Despite having fewer layers than other state-of-the-art models, the model outperformed them. In existing techniques for rice disease detection using drone-based mapping systems in agriculture, several technical gaps have been identified, prompting the design of the proposed methodology. Some of these gaps include limited spatial resolution, insufficient spectral information, and manual, time-consuming analysis. Many existing techniques cannot capture high-resolution images of rice fields. This limits the precision and accuracy of disease detection, especially for diseases that manifest as small localised patches or lesions. However, these methods may not capture the full range of spectral information required for accurate disease detection. The proposed methodology uses multispectral or hyperspectral sensors on drones to capture data across multiple spectral bands, enabling more comprehensive spectral analysis and the detection of subtle spectral changes associated with diseases. Manual analysis of large volumes of drone-captured data can be labour-intensive and time-consuming. Many existing techniques rely on expert visual interpretation, which can be subjective and prone to human error. The proposed methodology addresses this by incorporating automated image processing and analysis techniques, leveraging advanced algorithms and machine learning to analyse data efficiently and objectively.

3. Materials

3.1. Dataset Description

Five rice leaf diseases were employed in this study's dataset: bacterial leaf blight, leaf scald, and blast. One of the most devastating diseases that can affect a developing rice crop is brown spot, represented by the first label in the dataset [39]. The fungus "Bipolaris oryzae" is responsible for the sickness. The first sign is the emergence of dark or grey blotches in the leaf's midsection, surrounded by healthy yellow edges [40]. Spots caused by this disease may change in colour and size as the condition worsens, but their overall shape will remain round [41]. This means it has the potential to progress to the point where the entire leaf becomes yellow and dies. Consequently, brown spot disease causes both crop losses [42]. In contrast, disease-free rice is obtained from the healthy-labelled dataset. Now, the work discusses Hispa, an infection spread by the "Dicladispa armigera" bug, which is about as big as a dime and completely black [43]. Both the adult and the grub stages of this bug are harmful. The female insect spreads the illness by laying eggs singly near the base of the leaf. When the grub finally emerges, it will burrow into the leaf to reach the tissues between its layers, where it will eat. This digging causes the leaf to become white and membranous, and it eventually wilts and dies [44]; [38].

Figure 1: Sample images of the dataset

Finally, the dataset depicts leaf blast, a disease caused by the fungus "Magnaporthe Oryzae". All the parts of a rice plant that are above ground are vulnerable to this disease. The first sign of its impact is a crimson border around white or grey spots that appear on the leaf. Their usual form is a diamond with sharp corners. When the spots are big enough, they might cause the entire leaf. Figure 1 presents the sample images of the dataset.

4. Proposed Methodology

4.1. System Model

The system utilises a drone as the primary platform for data collection. The drone is equipped with a mapping system that includes sensors capable of capturing high-resolution images in different spectral bands, such as multispectral or hyperspectral sensors. The drone is also equipped with navigation and stabilisation systems for precise flight control. The suggested approach is among the few in the existing literature that can distinguish between six types. The average number of classes in a published work is between two and four. The photos will undergo a series of preprocessing steps in the proposed transfer learning-based technique, including background removal, resizing, and enhancement. The dataset size can also be increased through data augmentation. The majority of publications in the existing literature employ small datasets, as described in the literature review, which can lead to overfitting concerns. Data augmentation is used in this paper to create new photos by slightly altering the existing ones. Modifications of a somewhat small nature can take the form of rotation, scaling, and/or translation. Accuracy, precision, and the F1-measure are used to assess our method in this research. Described below are the specifics of the suggested transfer learning-based strategy.

4.2. Pre-Processing (Enhancement and Augmentation)

Both image enhancement and augmentation were used to improve and expand the original dataset. By flattening and adding detail in photos, the study may make them appear more compact and clearer. The edge-aware local contrast is adjusted to achieve this. This method preserves sharp edges by setting a lower bound on the intensity signal's amplitude. In this work, the enhancement value was set to 0.5 and the threshold to 0.15. To soften the sharp edges, an anisotropic diffusion filter is applied. The Fourier transform is used to move the zero-frequency component to the centre of the spectrum. Researchers must take great care to avoid overfitting whenever possible in machine learning studies. Several methods for addressing these problems are proposed in Verma et al. [45], including L1 and L2 regularisation, stochastic pooling, dropout, premature halting, and data augmentation. In this study, data augmentation is used to enhance the dataset size and hence mitigate overfitting. Using data augmentation is as easy as making little adjustments to the source photos to generate new ones. There are three easy ways to achieve results that visually resemble the source material. The term "rotation" suggests that the original picture will be rotated throughout the procedure. The photos are rotated by 15 degrees either way. The process of scaling in and out, respectively. Here, the height and width are increased by 105-115%, and finally, translate the picture along the x and y axes. In this case, the photos are shifted by a factor of -15 to +15.

4.3. Proposed Improved Swin Transformer for Classification

Specifically, the study presents a network that integrates the Swin Transformer and PolyLoss for automated identification of rice diseases in augmented images. In addition, the suggested method provides a visual interpretation based on the score-CAM approach. To improve the model's generalisation to new data, random data augmentation is applied to the training set. The improved images are then fed into the Swin Transformer in batches, with the model learning parameters and weights. The COA model, discussed further below, is also used to fine-tune the parameters. To further improve rice picture categorisation, PolyLoss is used to automatically adjust the polynomial coefficients. Score-CAM creates a graphical explanation of the model's reasoning based on the prediction.

4.3.1. Swin Transformer for Multi-Scale Feature Representation

By connecting a single token to all other tokens, the Transformer architecture used in image classification enables global self-attention. In contrast to networks, Vit18 does not preserve induction biases, such as locality or translational equivalence, within its neighbourhood. In particular, the two-neighbourhood structure characterises the adjacent areas of a picture that have common characteristics. Objectives in an image should provide the same effect (labels) regardless of where they are placed, a property known as translational equivalence. Researchers have shown that, with a sufficiently large sample size, inductive bias becomes apparent. While millions of medical photos have been labelled, accessing them is challenging owing to privacy and ethical concerns. Images require more processing power since their pixel resolution is substantially higher. To illustrate the multiscale features in rice leaf photos, the Swin Transformer is used in this study.

4.3.2. Architecture of Swin Transformer

An input image of size 224×224 is first divided into 224 non-overlapping 4×4 patches. Tokens are created for each patch and then projected to the C dimension using a linear embedding layer. These patch tokens are then subjected to two consecutive Swin Transformer computations to regulate the token count. A "stage" consists of the linear embedding layer and Transformer building elements working together. Similar to a CNN's layer structure, the Swin Transformer architecture halves the resolution at each stage while increasing the total number of channels. Swin-Transformer merges patch layers deeper into the network to decrease the amount of tokens needed to describe the hierarchy. The architecture of the proposed model is given in Figure 2.

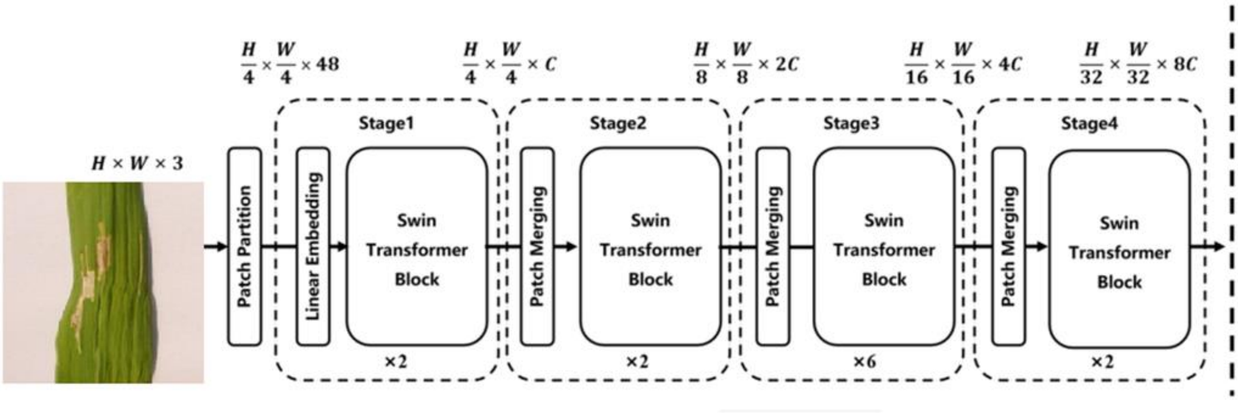

Figure 2: Swin transformer perfect structure

4.3.3. Swin Transformer Block

The Swin Transformer is a dual-unit structure. Multilayer perceptron (MLP) units have a self-attention module, a normalisation layer (LayerNorm), and an MLP layer. Swin Transformer is a block in ViT that swaps out the (MSA) module for two variants: the window (W-MSA) module and the shifting window module. A self-attention module, an MLP layer, and another normalisation layer (LayerNorm) make up a single unit. Both the first and second sections make use of the Window MSA (W-MSA) module; however, the former uses it in a shifted form, whereas the latter does not. Each MSA module and MLP layer is preceded by a LayerNorm layer, and a residual connection is used after each module. Figure 3 presents the layer architecture.

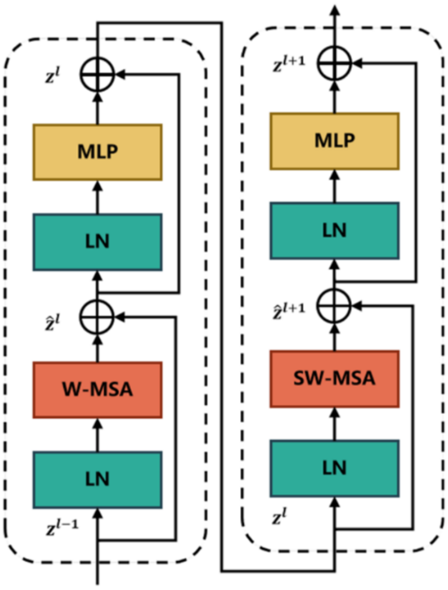

Figure 3: Layer architecture

To simplify calculation, the Transformer uses self-attention on windows. Standardised MSA is used internationally in ViT. Each patch's relationship to every other patch is calculated using this data. However, due to the huge number of patches, the computational complexity is quadratic, rendering it unsuitable for high-resolution photos. Transformer employs the W-MSA to determine the window, allowing for more accurate modelling. In comparison, a window is a collection of patches that cuts the picture in half in a regular, non-appearing manner. The computational complexity of the global MSA module and W-MSA in an image of hw patches is as follows, assuming Eq. (1) and Eq. (2):

$$\Omega(\mathrm{MSA}) = 4\mathrm{hwC}^2 + 2(\mathrm{hw})^2\mathrm{C} \quad (1)$$

$$\Omega(\mathrm{W-MSA}) = 4\mathrm{hwC}^2 + 2\mathrm{M}^2\mathrm{hwC} \quad (2)$$

C is the channel of patches, and h w is the sum of patches in the entire picture. The complexity in Eq. (1) is quadratic in the sum of patches, hw. When M is continuous (it is by default set to 7), the complexity of Eq. (2) is linear. Computing global self-attention for a large h × w matrix is typically prohibitively expensive, whereas window-based self-attention can scale indefinitely.

4.3.4. Shifted Window for Self-Attention

However, the modelling potential of the (W-MSA) is constrained by the absence of cross-window linkages. The Transformer block suggests a shift-window division approach to add cross-window connections without sacrificing the fast calculation of non-overlapping windows. To determine the local focus in the Swin Transformer's l-th layer, the study employs a window partitioning approach. The 88 into 22-sized panes. 4×4 (M=4). Then, the following layer $l+1$ accepts the window $\left(\left\lceil \frac{M}{2} \right\rceil, \left\lceil \frac{M}{2} \right\rceil\right)$ Pixels from the window. The new window's self-attention computation in layer l connects to the old window by traversing the old window's border. The subsequent Swin Transformer blocks are computed using the shifted window partitioning approach, as given in Eq. (3-6):

$$\hat{z}^{l} = W - MSA\left(LN\left(z^{l-1}\right)\right) + z^{l-1} \tag{3}$$

$$z^{l} = MLP\left(LN\left(\hat{z}^{l}\right)\right) + \hat{z}^{l} \tag{4}$$

$$z^{l+1} = SW - MSA\left(LN\left(z^{l}\right)\right) + z^{l} \tag{5}$$

$$z^{l+1} = MLP\left(LN\left(\hat{z}^{l+1}\right)\right) + \hat{z}^{l+1} \tag{6}$$

Where z^{l} and z^{l-1} stand for the W-MSA unit and MLP output features at the l layer, and where z^{l+1} stands for the MLP output features at layer l. The shift window division technique establishes the model's connection by introducing a link between the preceding layer. Some of the new windows created by the window-dividing approach are even smaller than MM. One common way for determining self-attention is to transform all available windows into MM. However, more windows will be created using this strategy. After applying the window transformation approach, the number of windows increases from 22 to 33, thereby increasing the model's computational burden. To address this issue, Swin Transformer proposes a cyclic shift in the top-left direction during batch computation. The window calculated in batches may include numerous non-adjacent windows in the feature map after shifting. Therefore, a masking technique is used to restrict the computation of self-attention to its respective sub-window. By maintaining a constant ratio of batch windows to normal window divisions, the cyclic shift enhances computing performance.

4.4. Chimpanzee Optimization Algorithm (COA)

The COA algorithm is a clever proposal inspired by the prey-hunting strategies of groups of chimpanzees. Individual chimpanzees are categorised as either a driver, barrier, chaser, or attacker based on the skills displayed throughout the hunting phase. Exploratory stages, such as repelling, blocking, and pursuing prey, make up the bulk of the chimpanzee group-hunting process. Attacking the prey is a key part of the development stage [46]. While it's true that different species of chimpanzee may reason independently and locate prey in different ways, it seems that, in the end, sexual behaviour in chimpanzees might confuse individual hunting behaviour [47]. The assumption is that the first chimpanzee to drive, barricade, chase, and attack knows where the prey will be, and that the others adjust their positions accordingly [48]. Equations (7) and (8) depict the mathematical model for how chimpanzees avoid and pursue prey:

$$d(t) = |cX_P(t) - mX_E(t)| \tag{7}$$

$$X_E(t+1) = X_P(t) - a * d(t) \tag{8}$$

Where X_P represents the prey's location, X_E Represents the chimpanzee's location, m represents the chaotic vector, t represents the sum of iterations, d(t) represents the distance between the chimpanzee and the prey, and a and c represent the constant vectors [49]. The values for a and c are found by solving Eqs. (9) and (10). When |a| is less than 1, the chimpanzee is focused on the prey; when it is greater than 1, the search area is widened:

$$a = 2 * f * r_1 - f \tag{9}$$

$$c = 2 * r_2 \tag{10}$$

Where r1 and r2 are chance facts taking values of $(0, 1)$, a is a chance variable among $[-2f, 2f]$, f is a linear meeting factor, and the cunning of the f formulation is Equation (11):

$$f = 2 - \frac{2*t}{t_{max}} \tag{11}$$

During the iterations, f deteriorates linearly after 2 to 0, and t_{max} It is the extreme sum of iterations. In the chimpanzee social hierarchy, the driver, barrier, chaser, and assailant all play a role. Equations (12)–(14) provide a mathematical model of a chimpanzee's attack on its victim:

$$\begin{aligned} D_A &= |c * X_A - m * X| \\ D_B &= |c * X_B - m * X| \\ D_C &= |c * X_C - m * X| \\ D_D &= |c * X_D - m * X| \end{aligned} \tag{12}$$

$$\begin{aligned} X_1 &= X_A - a * X_A \\ X_2 &= X_B - a * X_B \\ X_3 &= X_C - a * X_C \\ X_4 &= X_D - a * X_D \end{aligned} \tag{13}$$

$$X(t+1) = \frac{1}{4} * (X_1 + X_2 + X_3 + X_4) \tag{14}$$

Using the locations of the driver, barrier, chaser, and attacker, Equations (12) and (14) can be used to estimate the prey's location. As more chimpanzees move toward the prey, they continually adjust their posture. Once people in a group have eaten to their fill, a natural tendency to push chaos into the food supply emerges. To further address the two issues of local optima traps and sluggish convergence, the behaviour of chimpanzees at the last stage is helpful. Equation (15) illustrates the model formulation, which assumes a 50/50 chance of picking either the standard model to represent the chimpanzee's erratic behaviour:

$$X_E(t+1) = \begin{cases} X_P(t) - a * d, \mu < 0.5 \\ \text{Chaotic}, \quad \mu > 0.5 \end{cases} \tag{15}$$

Where μ takes the value of (0, 1), a random sum, and charting is used to inform the position. Figure 4 shows the mathematical function of the model.

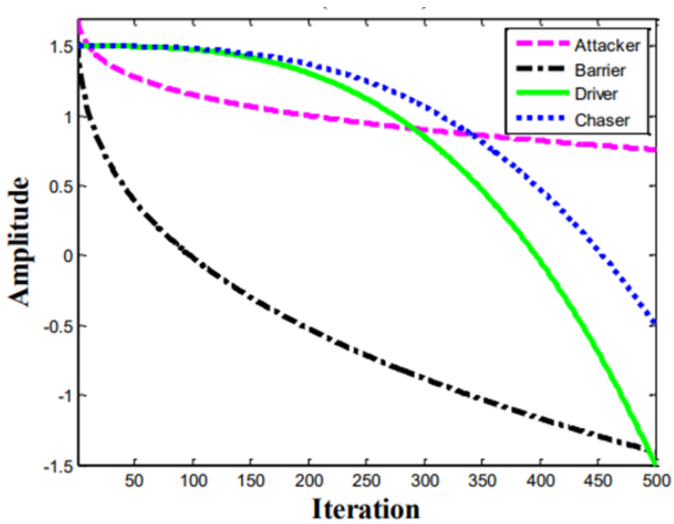

Figure 4: Mathematical function on the proposed optimisation model

The algorithm is provided for the COA model, which is shown below:

Algorithm1: COA

Initialize the chimp population x_i $(i = 1,2, \ldots, n)$
Initialise f, m, a, and c
Calculate the position of each chimp
Divide chimps randomly into independent groups
Until the stopping condition is satisfied
Calculate the fitness of each chimp
$x_{Attacker}$ =the best search agent
x_{Chaser} =the second-best search agent
$x_{Barrier}$ =the third best search agent
x_{Driver} = the fourth best search agent
while ($t <$ maximum number of iterations)
for each chimp:
Extract the chimp's group
Use its group strategy to update f, m, and c
Use f, m, and c to calculate a and then d
end for
for each search chimp
if ($\mu < 0.5$)
if ($|a| < 1$)
Update the position of the current search agent by Eq. (8)
else if ($|a| > 1$)
Select a random search agent
end if
else if ($\mu > 0.5$)
Update the position of the current search by Eq.(15)
end if
end for
Update f, m, a, and c
Update $x_{Attacker}, x_{Driver}, x_{Barrier}, x_{Chaser}$
t=t+1
end while
return $x_{Attacker}$

4.5. Map Generation Technique

The drone's GPS data was crucial in creating a detailed map of the rice paddies. The GPS readings displayed precise longitudes and latitudes [49].

Figure 5: Sample map generation in a rice field

The coordinates are mapped out using an enhanced version of Google Maps, as indicated in Table 1. Once the map has been created, it will be mapped against the analysed data from illness detection. Using GPS data attached to an actual photograph of a rice field, the system pinpoints the exact location of disease outbreaks. It displays a symbol that indicates the specific illness at that location. Figure 5 shows the sample map generation for a rice field.

Table 1: An example of the coordinates

	Coordinates	
No.	**Latitudes**	**Longitudes**
1	35.95292	139.6564
2	35.95233	139.65708
3	35.95198	139.65634
4	35.95243	139.65574

5. Experimentation, Results, and Discussion

Each model undergoes 200 training iterations. Model performance is measured relative to the most recent period. In addition, the study employs a weight-loss technique to reduce the likelihood of erroneous predictions caused by class imbalance in the rice dataset. Figure 6 presents the data distribution of the dataset.

5.1. Experimental Setup

Linux Ubuntu 16.04 with Pytorch 1.11.0 is used in the tests. An NVIDIA Tesla V100 GPU is used for the training of the models. The study uses Xavier initialisation to set the weights, then optimises them using Adam during training with a learning rate of 0.900. The initial learning rate is 2e4 and eventually decreases to 1e5. The original-sized rice leaf photographs have all been scaled down to 224224. The quantity per batch was fixed at 32. Figure 6 presents the distribution of the dataset.

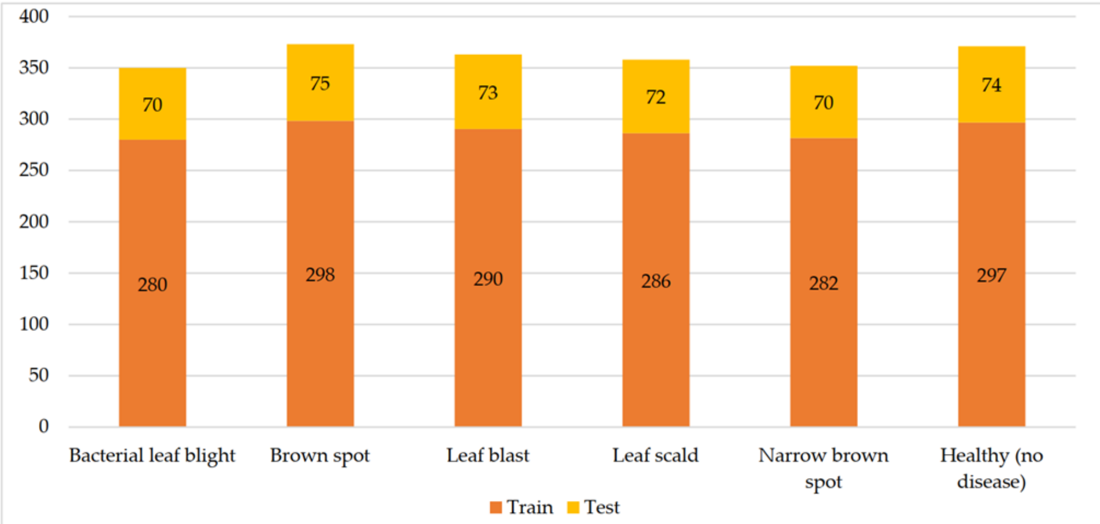

Figure 6: Data distribution on the dataset [49]

5.2. Performance Metrics

In this experimental analysis, different parameters were used, including Accuracy, Precision, Recall, Specificity, and F1_score. Logits are transformed into class probabilities using the softmax function, and the category with the highest probability is used to evaluate classification performance. Evaluation criteria. Metrics for assessment are calculated as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (16)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (17)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (18)$$

$$\text{F1} - \text{Score} = 2.\frac{\text{precision.recall}}{\text{precision+recall}} \tag{19}$$

Where TP stands for "true positive," TN for "true negative," FP for "false positive," and FN for "false negative." In the four-class rice disease classification, true positives (TP) are the number of samples that the model properly labels as belonging to one of the four classes, false positives (FP) are the sum of examples that the model labels as belonging to one of the four classes other than the correct one, and false negatives (FN) are the sum of samples that the model labels as belonging to a class other than the correct one. Further evaluation of the suggested approach may be conducted by calculating the area under the curve (AUC). A higher AUC indicates better prediction accuracy. Because most prior methods only split rice diseases into two categories, this study explores general DL models.

5.3. Results

Table 2 provides a comprehensive comparison of DL models across both sets.

Table 2: Analysis of various models using 50%-50%

Methods	Accuracy	Precision	Recall	Specificity	F1_score
DBN	83.87%	0.8373	0.8405	0.9677	0.8379
CNN	88.72%	0.8885	0.8889	0.9775	0.8836
RNN	87.10%	0.8675	0.8725	0.9742	0.8681
LSTM	86.18%	0.8764	0.8629	0.9722	0.8554
Chimpanzee-based ST	89.86%	0.9005	0.9005	0.9797	0.8986

In the accuracy analysis, existing techniques, such as DBN, CNN, RNN, and LSTM, achieved 83% to 86%, whereas the proposed Swin transform achieved 89.86%. In this analysis, various DL models attained 82% to 89% precision, 90% recall, and 89.86% F1-score. The reason for poor performance is that fewer training and test data are used for validation. Table 3 presents the analysis for the 70%-30% split of the data.

Table 3: Performance analysis of different classifiers using 70%-30%

Methods	Accuracy	Precision	Recall	Specificity	F1_score
DBN	83.41%	0.8460	0.8364	0.9668	0.8368
CNN	88.33%	0.8795	0.8833	0.9767	0.8797
RNN	87.14%	0.8723	0.8714	0.9743	0.8677
LSTM	92.38%	0.9255	0.9238	0.9848	0.9233
Chimpanzee-based ST	94.24%	0.9433	0.9435	0.9885	0.9431

When the training data is high and the test data is low, all models perform well. For instance, the projected model achieved 94.24% precision, Recall, accuracy, and F1, whereas the same perfect model achieved 98.85% specificity. The existing techniques also achieved better performance than Table 2. The rationale for the improved performance is that the Swin Transformer outperforms prior models by incorporating window partitioning and connecting neighbouring non-overlapping Windows, thereby integrating functionality. Also, by improving the cross-entropy loss via Taylor expansion, the Poly loss further enhances performance. It adjusts a large number of polynomial bases based on the task and dataset to control the significance of each basis. The validation analysis for various models with 80%-20% is presented in Table 4.

Table 4: Comparative analysis of the proposed model for 80%-20%

Methods	Accuracy	Precision	Recall	Specificity	F1_score
DBN	86.90%	0.8721	0.8690	0.9738	0.8675
CNN	92.63%	0.9306	0.9272	0.9852	0.9251
RNN	91.38%	0.9255	0.9238	0.9848	0.9233
LSTM	94.76%	0.9501	0.9476	0.9895	0.9475
Chimpanzee-based ST	96.01%	0.9626	0.9614	0.9921	0.9609

On the 80%-20% validation set, the suggested Swin-Transformer and existing approaches perform similarly. Additionally, the Swin-Poly Transformer's test accuracy is higher than that of the currently used methods. Additionally, the Swin-Poly Transformer's accuracy curve outperforms other models on the training set in the first 50 iterations. These phenomena imply that the use of Poly loss enhances generalisation and resilience. Understanding the mechanics of decision-making and disclosing learned traits is easier when you see intermediate levels. Vision interpretability is a developing field that has the potential to give model developers new insights into how models function and new ways to identify predicted failures. In typical photos, the model appears to focus on the entire layer, demonstrating its ability to learn intricate and representative aspects of the layer. These visualisation findings are clear and impressive overall, demonstrating the suggested model's ability to correctly identify regions of interest. Finally, the precision of 0.96 for the proposed method's best performance shows that the addition of Poly loss enhances performance. The graphical comparison of the projected model with the available methodologies is shown in Figures 7-11.

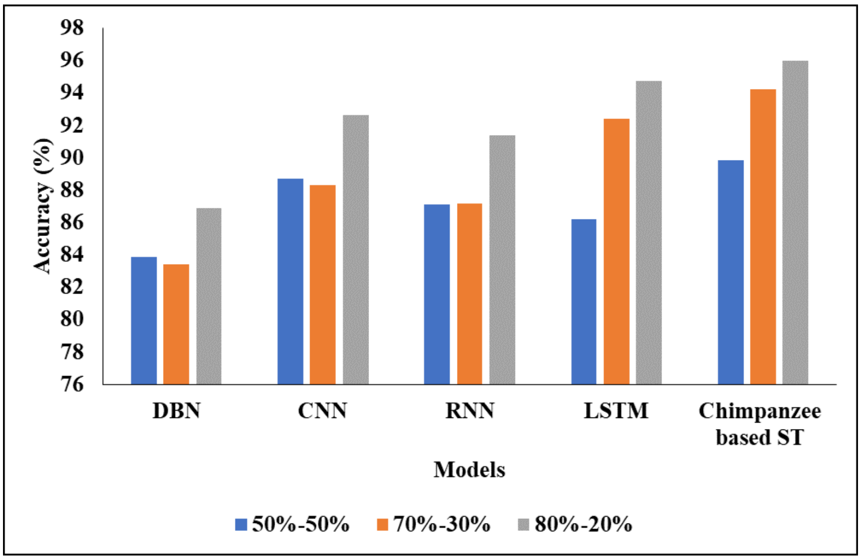

Figure 7: Accuracy analysis

In Figure 7, the accuracy analysis shows that the proposed model achieved better accuracy than the other compared models. When the data is 50-50, the existing models achieve 83%-87%, while the proposed model achieves 89%. When the data is split 80% to 20% between training and testing, the existing models, such as CNN, RNN, and LSTM, achieve nearly 91% to 94%, and the DBN achieves 86%. However, the proposed model achieved 96% accuracy and performed better through hyperparameter optimisation.

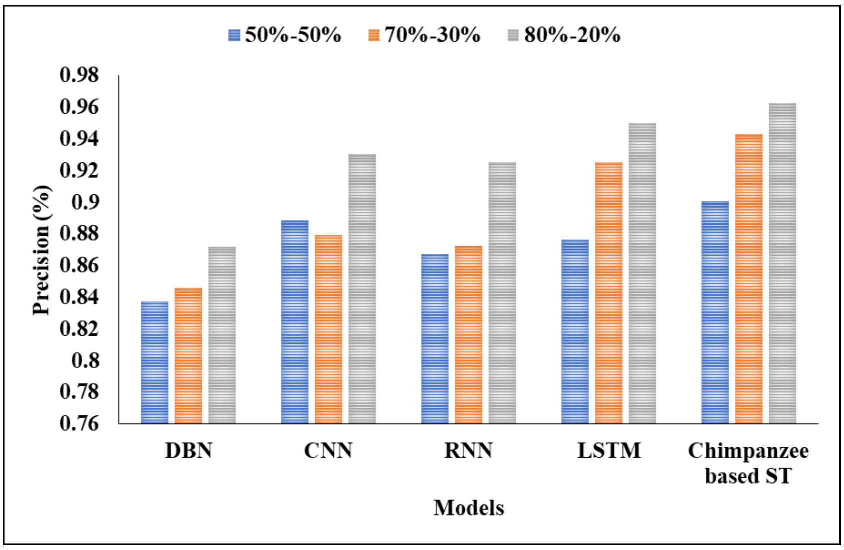

Figure 8: Analysis of different models

In Figure 8, the accuracy Analysis of different models is shown; however, the proposed model achieved better results than the others. For instance, LSTM achieved 92% accuracy, precision, Recall, and F1-score; RNRecallCNN achieved 87%-88%

accuracy, precision, Recall, and F1-score. In a recall analysis of specificity, the existing DBN model achieved 96%, the CNN and RNN models achieved 97%, the LSTM model achieved 98%, and the proposed model achieved 98.85%.

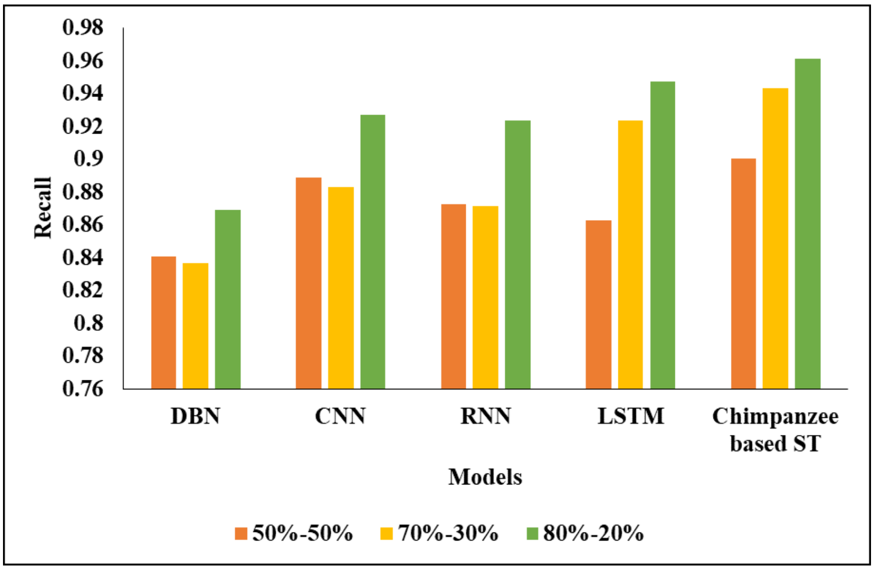

Figure 9: Recall analysis

In Figure 9, the Recall analysis shows that the proposed model outperforms the others; however, it achieves a higher Recall than they do. When the training set is 80%, and the test set is 20%, the proposed model achieved 96% recall, whereas existing models such as LSTM, RNN, and CNN achieved 94% and 92%, respectively. These same models achieved 94% for the proposed method, 88% for CNN, 87% for RNN, and 92% for LSTM when the training and test data were split at 70% and 30%, respectively. This analysis clearly shows that data plays a major role in the model's performance.

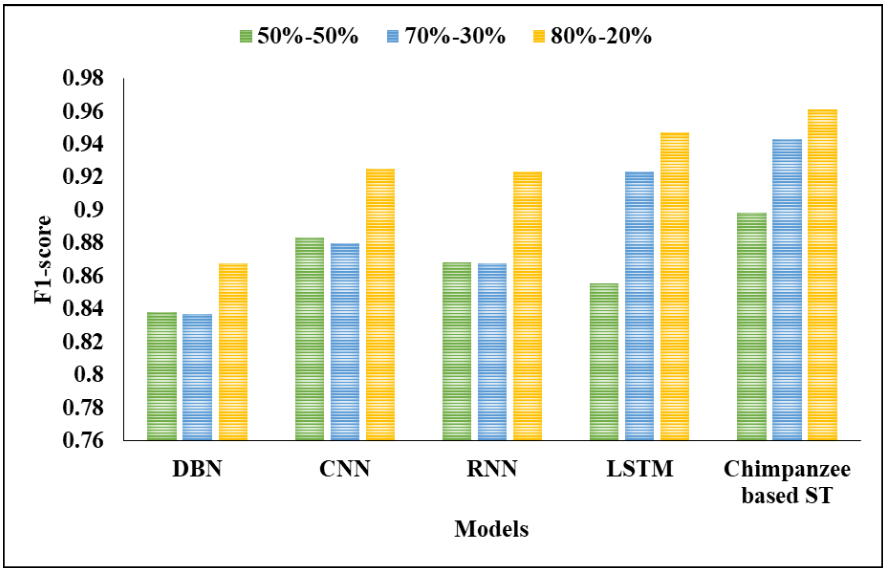

Figure 10: F-score comparison

Figure 10 above shows the F-score analysis of the proposed model compared with other models; however, the proposed model achieved a higher F-score than the others. When the data is low, the performance of all techniques is also low, and the models achieve better performance as the data size increases.

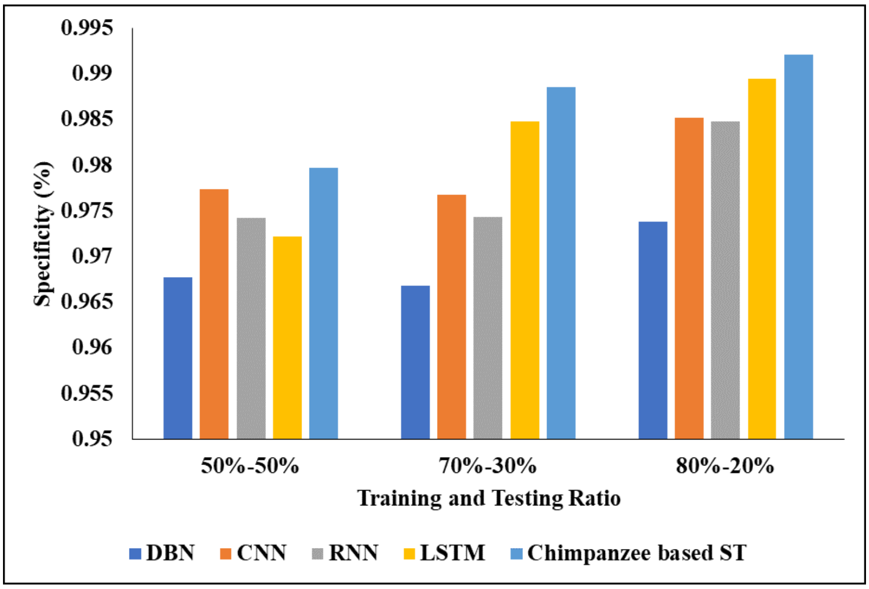

Figure 11: Specificity analysis

In Figure 11, the Specificity analysis shows that the proposed model has better specificity than the other compared models. In terms of specificity, the proposed model achieved nearly 97%, 98%, and 99% for 50-50, 70-30, and 80-20, respectively. Likewise, the existing models achieved 96% for 50-50, 97% for 70-30, and 98% for 80-20. Table 5 presents the timing analysis of the proposed model across various training and testing datasets.

Table 5: Timing analysis for the proposed model

Proposed Model	Pre-Training	Post-Training
50%-50%	12.91 ± 0.47	12.15 ± 0.54
70%-30%	13.39 ± 0.19	12.97 ± 0.15
80%-20%	5.62 ± 0.42	7.62 ± 0.42

When the model is pre-trained, it takes 12.91s for 50%-50% training and testing data, 13.39s for 70%-30%, and 5.62s for 80%-20%. For post-training analysis, the proposed model achieved 12.15s for 50%-50%, 12.97s for 70%-30%, and 7.62s for 80%-20% on complete rice leaf images, both for training and testing.

5.4. Analysis

The use of drones equipped with mapping systems enables early detection of rice diseases. By regularly monitoring crops from above, diseases can be identified at early stages before visible symptoms appear on the ground. This allows for prompt intervention and reduces the risk of significant crop damage. The study finds that the proposed model emphasises the aberrant portions of the image. In addition to showing the lesion of interest, the confidence score map also shows the area surrounding the abnormality, suggesting that the near situation may be helpful for prediction. In typical photos, the model appears to focus on the entire layer, demonstrating its ability to learn intricate and representative aspects of the image.

6. Conclusion and Future Scope

Plant diseases are often easiest to observe on their leaves. Leaves affected by various illnesses exhibit unique characteristics. More than half of humanity depends on rice as its primary source of nutrition, making rice cultivation critically vital. Plant diseases severely impact the quality and yield of rice. The annual yield loss due to rice diseases is estimated at 20%-40%. Early diagnosis by manual identification of these illnesses requires farmer-specific disease knowledge and the laborious process of visually inspecting broad farmlands with individual rice crops. It's hard to see this being done, and even if it could, the cost would likely drive up rice prices for everyone. An automated system that can perform early detection and reduce costs is an option. Recent advances in computing have propelled the field of computer vision. Visually distinguishable symptoms of rice leaf disease can be employed as characteristics for systems. This study proposes an effective Swin-Poly Transformer for the accurate documentation and analysis of six classes, including healthy rice leaves, enabling the diagnosis of five rice illnesses from leaf photos. The network can upgrade the simplistic categorisation model to one that is both analytical and adaptable, with hyperparameters (COA model) optimised through a cost-benefit analysis. The rice leaf dataset consists of healthy leaves and five diseases, including narrow brown spots, leaf scalds, leaf blasts, brown spots, and bacterial leaf blight. The proposed model achieved 96% accuracy, precision, Recall, and F1-score on a 20%- 80% split, whereas the existing models achieved 94%-95% across these metrics. InRecalluture, the study will develop a fully functional scheme that can be evaluated in real-world, real-time settings, and is underpinned by drone technology. Here are some areas of future development and exploration. Additionally, it is intended to investigate plant diseases crucial to human survival and linked to the agricultural sector. The future may see the development of autonomous drone systems capable of planning and executing flight missions independently.

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Ethics and Consent Statement: The study was conducted in full compliance with established ethical standards, including informed consent, participant confidentiality, and responsible data handling throughout the research process.

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