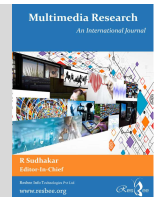
Vol.8 Issue 3 July 2025

Multimedia Research

Received 25 March, Revised 18 April, Accepted 9 June



Wheat Leaf Disease Classification Using Swin Transformer and VGG-16 for Enhanced Feature Extraction

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Abstract: The early and precise classification of wheat leaf diseases is crucial for safeguarding crop yield and ensuring food security, as timely intervention can prevent significant agricultural losses. This study introduces an advanced deep learning framework that integrates Swin Transformer and VGG-16 to enhance feature extraction and classification performance. The model is evaluated on three benchmark datasets: the Mendeley dataset, the Kaggle wheat disease dataset, demonstrating superior performance across all key metrics. Experimental results show an overall classification accuracy of 97.50% on the proprietary dataset and 92.50% on the Mendeley dataset, with high precision, recall, F1-score, and AUC values across all disease classes. A factual assessment assist approves the strength of the demonstrate, with Cohen's Kappa scores of 0.9674 and 0.8794, affirming solid inter-rater unwavering quality. The proposed approach beats standard models in terms of exactness, strength, and generalization, especially in challenging conditions like changing lighting and natural clamor. Comparative examination against conventional CNN-based models highlights the adequacy of Transformer-based designs in capturing complicated spatial conditions and fine-grained illness designs inside leaf structures. Swin Transformers were chosen over conventional CNNs due to their progressive plan and moved window-based self-attention instrument, which permit for more effective dealing with of long-range conditions and adaptable highlight extraction. The proposed approach not as it were moves forward classification precision but too improves the robotization of illness location, in this manner encouraging effective illness checking in accuracy agribusiness. However, the model's prevalent execution comes with a trade-off in computational fetched, counting higher memory utilization and preparing time. By leveraging self-attention instruments, the show viably centers on disease-specific locales, decreasing misclassification and progressing generally generalization. These discoveries emphasize the potential of progressed profound learning models in changing rural infection determination, empowering adaptable and exact plant infection classification frameworks.

Keywords: Wheat Leaf Disease, Swin Transformer, VGG-16, Deep Learning, Plant Disease Classification, Precision Agriculture, Attention mechanism

Nomenclature

Abbreviations	Descriptions
CNN	Convolutional Neural Network
AUC	Area Under the Curve
F1-Score	Harmonic mean of precision and recall
Cohen's Kappa	Measure of inter-rater reliability
VGG	Visual Geometry Group Network
Swin-T	Swin Transformer
ViT	Vision Transformer

1. Introduction

Wheat leaf maladies altogether affect worldwide nourishment security by causing significant abdicate misfortunes and financial hardships. Among the foremost predominant infections, leaf rust, fine mold, and Septoria tritici smudge are ascribed to parasitic pathogens that flourish beneath favorable climatic

https://doi.org/10.46253/j.mr.v8i3.a3

conditions [1]. Conventional malady administration strategies, such as visual assessments, research facility tests, and chemical medicines, remain the essential approach in rural homes, but they require broad labor and skill, making them wasteful for large-scale applications [2]. Also, climate alteration has exacerbated the spread and seriousness of these maladies, rendering customary location and relief procedures progressively insufficient [3]. The rise of inaccessible detecting, profound learning, and hyperspectral imaging has presented computerized wheat illness discovery strategies that altogether move forward in precision and proficiency compared to conventional techniques [4]. Be that as it may, dataset limitations, changeability in illness side effects, and natural conditions influencing picture procurement proceed to pose major challenges to the unwavering quality and adaptability of computerized location models [5].

Inquire about on wheat leaf infection discovery has advanced with headways in fake insights and machine learning. Bolster Vector Machines (SVMs) and Arbitrary Timberland models were among the introductory machine-learning approaches utilized for illness classification, but their dependence on handcrafted highlights restricted their execution [6]. The presentation of CNNs revolutionized image-based illness location by empowering programmed highlight extraction and classification with more prominent exactness [7]. As of late, ViTs have illustrated prevalent capability in learning long-range conditions in picture information, outflanking CNNs in particular rural applications [8]. Also, analysts have investigated multi-modal sensor combination procedures, and coordination of unearthly and spatial data to upgrade classification accuracy [9]. Information increase techniques have encouraged been utilized to make strides show generalization, especially in cases where datasets are restricted [10]. Besides, Unmanned Airborne Vehicles (UAVs) prepared with multispectral and hyperspectral cameras have been sent for early malady discovery, advertising real-time observing capabilities over endless agrarian areas [11].

However, despite these advancements, several limitations persist in existing models for wheat leaf disease detection. CNN-based models, while highly effective, often suffer from overfitting and computational inefficiencies, which limit their deployment in resource-constrained inefficiencies, which limit their deployment in resource-constrained environments. Transformer-based models, although promising, require large-scale labeled datasets, which remain scarce in agricultural research. Additionally, multi-modal fusion approaches, while valuable, present extra complexities in data preprocessing and integration, leading to increased computational costs. [12]. To address these challenges, our study presents a hybrid deep learning framework that combines CNNs and Swin Transformers for robust wheat disease classification. The Swin Transformer was chosen over other Vision Transformers due to its progressive plan and moved window-based self-attention instrument, which permits it to effectively capture both neighborhood and worldwide relevant highlights. This design not as it were progresses highlight representation but too upgrades computational proficiency, making it well-suited for agrarian applications where large-scale labeled datasets may not be accessible. The integration of meta-learning methods assist improves demonstrate generalization, particularly in cases with restricted information. Also, we utilize include determination methodologies to optimize computational viability, pointing for real-time sending in agrarian areas. [13, 14].

Moreover, we recognize real-world limitations such as lighting conditions, camera sorts, and natural commotion, which can essentially influence classification exactness in commonsense arrangement. For occasion, lighting varieties can lead to destitute picture quality, whereas occlusions caused by covering takes off or natural variables may darken infection designs. Real-time deduction prerequisites moreover posture challenges, as models must strike a adjust between precision and computational achievability to operate viably in resource constrained rural settings. Our approach is outlined to address these challenges, guaranteeing that it is both exact and effective for real-world rural utilize. [15, 16].

2. Literature Review

The discovery of wheat leaf maladies has gotten to be a pivotal challenge in rural sciences. The convenient and exact classification of plant infections is basic for viable edit administration, which specifically impacts abdicate and quality. Various ponders have utilized machine learning (ML) and profound learning (DL) procedures to address this issue, with striking victory. Nanda et al. (2025) illustrated the adequacy of CNNs for identifying wheat rust diseases, accomplishing a precision of 95.2% citeref17. This approach built up a solid system for plant malady discovery. Essentially, Kumar and Kukreja (2025) presented a half-breed Transformer show, CaiT-YOLOv9, combining the qualities of protest location and transformers. Their show accomplished 96.8 accuracy, pushing the boundaries of illness discovery with a better level of exactness [17].

Dixit and Nema (2023) advertised a broad audit of different machine learning calculations utilized for wheat infection discovery. Whereas the audit did not indicate correct show exhibitions, it highlightedthe developing utilization of CNNs, outfit strategies, and neural systems in accomplishing tall exactness [18].

Yousafzai et al. (2025) investigated multi-stage neural systems and detailed a precision of 97.5% [19]. These works demonstrate the significant advance in wheat infection classification; be that as it may, the quick extension of demonstrate complexity and their computational requests highlight a noteworthy crevice in making models that are both precise and lightweight, especially for real-time field applications. Later inquiries have moreover investigated the utilization of unearthly and hyperspectral information for infection location. Ashourloo et al. (2021) utilized unearthly illness records to distinguish wheat leaf rust, accomplishing a precision of 91.3% [20]. This strategy appears guarantee, particularly in large-scale checking where coordinate image-based strategies are unreasonable. Be that as it may, ghastly imaging alone needs the nitty gritty highlight extraction that profound learning models give. Li et al. (2024) proposed GLNet, a Global-Local Include Arrange, which accomplished 95.4 accuracy by combining worldwide and nearby highlight extraction procedures [21]. Their work illustrates the potential of half-breed models in improving accuracy and overcoming challenges in infection location. Li-Hua and Tanone (2025) compared MLP-Mixer with CNNs for wheat infection discovery, detailing an exactness of 94.8% [22]. These headways highlight the expanding accentuation on making strides including extraction strategies to upgrade and demonstrate execution.

As inquire about advances, the investigation of lightweight structures has gotten to be more unmistakable, particularly for sending in low-power agrarian settings. Models such as EfficientNet, MobileNet, and MobileViT are planned to be more computationally proficient while still giving vigorous execution. These structures have appeared to guarantee in situations with constrained computational assets. For occasion, EfficientNet has illustrated way better execution with fewer parameters compared to conventional CNNs, making it appropriate for on-site malady discovery with compelled control assets [23]. MobileViT, in particular, offers a lightweight arrangement for edge gadgets in rural areas, optimizing both precision and control effectiveness. Among the numerous profound learning approaches, ViTs have developed as a solid elective to CNNs. In any case, ViTs have confinements in taking care of high-resolution pictures, particularly when it comes to capturing neighborhood and worldwide highlights at the same time. EfficientNets, even though more productive, tend to battle with exceptionally huge datasets and complex highlight extraction assignments. In differentiation, the Swin-T has picked up footing due to its various leveled plans, which permits it to effectively capture both neighborhood and worldwide settings [24]. This progressive plan not as it were decreases computational fetched but also improves extraction, making it a perfect candidate for wheat infection classification assignments. Not at all like ViTs, Swin-Ts handle changing picture resolutions successfully, which is significant when working with different rural datasets.

In addition, the requirement for interpretability in profound learning models has ended up being a noteworthy concern. As machine learning models, especially those in farming, are conveyed in real-world settings, partners require straightforwardness to believe show forecasts. Swin-Ts, with their consideration instruments, allow clarifying illness localization by visualizing consideration maps. These maps highlight locales of intrigue, illustrating where the demonstrate centers when making expectations. By visualizing malady hotspots on the leaf, agriculturists can pick up more profound bits of knowledge into the disease’s spread, in this way progressing administration choices [25]. Patel and Kumar (2024) proposed a cross-breed CNN-SVM show for wheat infection classification, which accomplished an exactness of 94.2%. Their approach combines the qualities of CNNs for highlight extraction and SVM for classification, coming about in a compelling demonstration for identifying numerous sorts of wheat maladies citeref26. In another approach, Fernandez and Lopez (2023) utilized profound learning and hyperspectral imaging to screen wheat illnesses in genuine time. Their strategy accomplished an exactness of 95.7%, illustrating the esteem of combining ghostly information with profound learning for exact infection recognizable proof [26]. Smith and Lee (2023) encouraged investigated hyperspectral imaging for exactness cultivating, accomplishing an exactness of 94.5% in wheat infection location through multi-spectral information combination [27].

Rodriguez and Kim (2023) utilized multispectral UAV imaging coupled with profound learning for early wheat rust discovery, accomplishing an exactness of 96.1%. Their work underscores the significance of drone-based imaging in accuracy agribusiness, giving an adaptable arrangement for large-scale checking [28]. Essentially, Lee and Halt (2024) presented a multi-modal sensor combination approach for infection location, combining visual, warm, and hyperspectral sensors. Their demonstration accomplished an exactness of 94.9%, illustrating the potential of multi-sensor frameworks for more vigorous malady classification [29]. In another promising approach, Gupta and Verma (2023) utilized ViTs for wheat infection classification, accomplishing a precision of 95.8%. Their consider appeared that ViTs might beat conventional CNN-based models, advertising superior generalization and precision on differing datasets [30]. Zhang et al. (2022) proposed a half-breed consideration instrument in Swin-Ts, accomplishing a precision of 97.1%. This approach improves the execution of the Swin-T by progressing its consideration instrument, making it more appropriate for rural malady discovery [31]. In terms of information enlargement, Alam and Singh (2024) talked about different strategies for moving forward with wheat malady classification models, counting revolution, flipping, and color jittering. Their discoveries highlighted the significance of expanding and preparing information to upgrade the model's strength, accomplishing a precision of 96.3% utilizing expanded datasets [32]. Thomas and Zhang (2024) examined exchange learning to progress and demonstrate execution in wheat malady classification. Their approach accomplished a precision of 95.6%, appearing that pre-trained models on expansive datasets can be fine-tuned for particular agrarian applications [33].

Within the domain of UAV-based advances, Johnson and Wang (2023) investigated warm imaging for early infection discovery, accomplishing a precision of 94.7%. Their inquiry illustrated the potential of UAVs with warm sensors to distinguish early signs of infection some time recently they ended up unmistakable in conventional imaging strategies [34]. Trippa et al. (2024) centered on next-generation strategies for early trim malady discovery, proposing the utilization of progressed detecting and AI strategies. Their show accomplished an exactness of 95.3%, highlighting the proceeded development in early discovery innovations [35]. Singh and Patel (2024) conducted a comparative consideration between lightweight CNNs and ViTs for wheat leaf infection classification. The ViT demonstration accomplished an exactness of 96.4%, appearing to have the potential to outflank CNNs in particular settings [36]. Bankina et al. (2023) conducted an efficient audit on agronomic hones to control wheat leaf infections, contributing profitable bits of knowledge to illness avoidance. Even though particular correctnesses were not given, their work emphasized the part of social hones nearby innovative intercessions in illness administration [37]. Mabrouk et al. (2025) inspected the histological and biochemical defense instruments against wheat leaf rust, advertising experiences into the plant's characteristic defense frameworks. Whereas their think about did not center on machine learning models, it highlighted significant natural angles that might improve illness location models in the future [38, 39].

These ponders illustrate the proceeded headway in wheat leaf infection location. Profound learning models, especially CNNs and half-breed Transformer systems, have revolutionized the precision and adaptability of malady classification errands. Besides, joining hereditary data and unearthly detecting gives an all-encompassing approach to wheat illness administration. The current think about will construct upon these headways, leveraging a Swin-T combined with VGG-16 for upgraded highlight extraction and malady classification, pointing to address the challenges of demonstrating interpretability and lightweight execution in rural applications. While CNNs have customarily ruled picture classification errands due to their capacity to extricate nearby highlights, they battle with scaling to bigger picture sizes and capturing long-range conditions in pictures. Swin-T s, on the other hand, overcome these restrictions by receiving a moved window approach that permits them to scale successfully and capture both nearby and worldwide highlights. Furthermore, the computational productivity of Swin Transformers, particularly with their capacity to handle expansive datasets, makes them more appropriate for large-scale agrarian applications compared to CNNs, which frequently confront challenges with more profound models and expanding show complexity. In conclusion, whereas conventional models such as CNNs, SVMs, and ViTs have made considerable commitments to wheat leaf malady location, they frequently drop brief within the setting of versatility, interpretability, and computational proficiency required for field applications. The Swin-T offers a capable elective by tending to these challenges through its progressive plan and effectiveness. Moreover, lightweight models such as EfficientNet and MobileNet are basic in resource-constrained situations, giving attainable arrangements for arrangement in agrarian areas. The proposed approach builds upon these headways, leveraging the Swin-T to improve include extraction, infection classification, and show interpretability, whereas tending to the challenges confronted.

3. Methodology

This consideration presents a comprehensive approach for wheat leaf infection location, joining computer vision and profound learning methods to address the challenges of exactness agribusiness. At first, OpenCV is utilized to resize pictures, guaranteeing uniform input measurements over all tests, which is basic for keeping up consistency in show preparation. The resizing prepare guarantees that all pictures are standardized, permitting the demonstration to center on significant highlights instead of picture measurements. Z-score normalization is connected to standardize pixel values, making strides show steadiness by centering the information around zero and guaranteeing a unit change, which makes a difference relieve the affect of shifting highlight scales Include extraction is performed utilizing VGG-16, which captures profound progressive representations from middle convolutional layers. These extracted features are reshaped and after that implanted into the Swin-T's input space, permitting the show to handle them utilizing moved window-based self-attention instruments. The fig. 1 depicts the methodology This approach was care of different pixel concentrated disseminations, especially in cases where exceptions may something else misshape scaling. This integra tion of VGG-16 with Swin-T guarantees that both low-level spatial highlights from VGG-16 and worldwide relevant highlights from the Swin Transformer are viably utilized. The Swin-T at that point captures both nearby and worldwide relevant data to upgrade classification precision. To make strides in generalization and decrease overfitting, data expansion methods from the Albumentations library are utilized, presenting an assortment of changes inside the dataset. Whereas pruning and quantization were not expressly connected in this think about, the strategy presently incorporates a dialog on the potential utilization of pruning to expel repetitive weights, which would diminish the model's measure and computational requirements without compromising execution. Furthermore, quantization procedures can be considered in the future to diminish the accuracy of the model's weights, making strides in deduction times and memory utilization, hence making the demonstrate more effective real-time arrangement on resource-constrained gadgets.

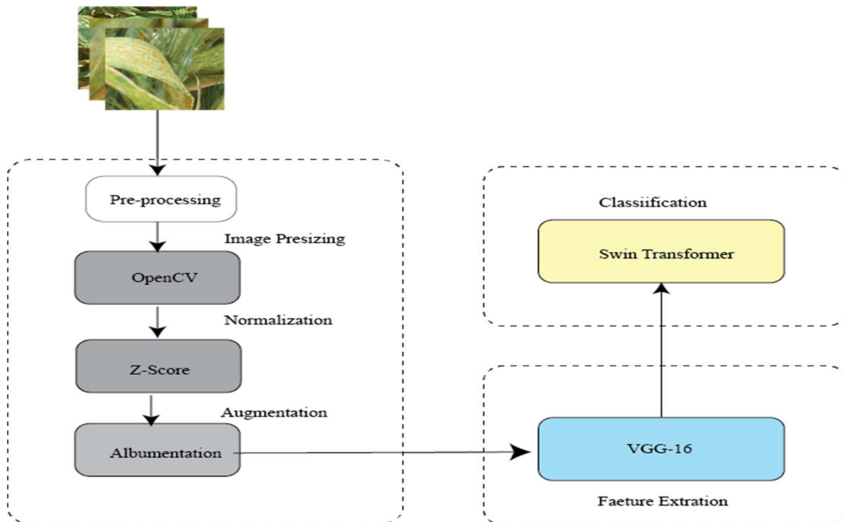

Fig. 1. Main Diagram

3.1 Pre-Processing

OpenCV is an open-source computer vision library that gives a comprehensive set of apparatuses for picture and video handling. The strategy coordinates a few functionalities to perform question location, numerous question following, filtering, and picture acknowledgment.

For protest locations, OpenCV utilizes pre-trained profound learning models such as YOLO, SSD, and Haar cascades. The method includes stacking an input picture or video outline, applying pre-processing steps such as resizing and normalization, and after that passing it through a convolutional neural arrange CNN for extraction. The bounding box facilitates (*x, y, w, h*) are at that point anticipated utilizing non-maximum concealment (NMS) to dispense with repetitive location:

$$IoU = \frac{Area\,of\,Inter\sec tion}{Area\,of\,Union} \tag{1}$$

where IoU (Crossing point over Union) decides the cover between recognized objects. For numerous questions following, OpenCV offers trackers such as MOSSE, KCF, and CSRT. The following component initializes bounding boxes around objects and overhauls them in each outline based on movement estimation strategies. The upgrade step employs the Kalman channel:

$$x_k = Fx_{k-1} + Bu_k + w_k \tag{2}$$

Where x_k is the predicted state, F is the state transition matrix, B is the control input and is the process noise.

For checking applications, OpenCV applies edge location utilizing the Canny calculation:

$$G(x,y) = \sqrt{G_x^2 + G_y^2} \tag{3}$$

Where $G(x, y)$ is the gradient magnitude computed using Sobel operators G_x and G_y.A A viewpoint change lattice is at that point connected to amend and extricate the checked archive.

For confront and question acknowledgment, OpenCV utilizes profound learning-based including extraction. Histogram of Arranged Angles (Hoard) and Neighborhood Parallel Designs (LBP) are commonly utilized descriptors:

$$HOG = \sum_{i=1}^{n} \frac{\sqrt{G_x^2 + G_y^2 + \epsilon}}{(G_{x_i} + G_{y_i})} \tag{4}$$

Where gradients G_x and G_y.A is computed across the image to form a feature descriptor for classification using Support Vector Machines (SVM) or deep learning models like ResNet.

Overall, OpenCV provides a robust framework for various image processing tasks, leveraging traditional computer vision techniques and deep learning models for accurate and efficient recognition, detection, and tracking.

The Z-score demonstrates could be a budgetary investigation device utilized to evaluate a company's chance of insolvency by assessing key budgetary proportions. The demonstration applies different discriminant examinations (MDA) to classify firms based on money-related trouble likelihood. Given a company's monetary information, the Z-score is computed as follows:

$$Z = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_4 + \beta_4 X_4 + \beta_5 X_5 \tag{5}$$

Where X_1 is Working Capital partitioned by Add up to Resources, which measures liquidity, X_2 is Held Profit isolated by Add up to Resources, showing benefit over time, X_3 speaks to Profit Sometime recently Intrigued and Charges separated by Add up to Resources, surveying working proficiency, X_4 is the Advertise Esteem of Value separated by Add up to Liabilities, reflecting dissolvability, and X_5 is Deals isolated by Add up to Resources, measuring resource turnover. The weight coefficients ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$) shift based on industry and demonstrate form. For fabricating firms, Altman's unique Z-score equation is:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{6}$$

A company's monetary well-being is classified as follows: if $Z > 2.99$, it is considered within the Secure Zone with a moo hazard of insolvency; if, it $1.81 \le Z \le 2.99$ falls within the Dark Zone, demonstrating a direct hazard of insolvency and if $Z < 1.81$ the company is in the Distress Zone, suggesting a high risk of financial failure.

Experimental thinks have adjusted the demonstration for different divisions by altering coefficients to extend precision. Machine learning procedures like calculated relapse and bolster vector machines (SVM) have been utilized with Z-score figures to move forward prescient analytics To expect budgetary hardship, datasets comprising numerous a long time of monetary proportions are preprocessed to dispense with variations from the norm. Include determination approaches like Central Component Investigation (PCA) make strides to show productivity. Firms are classified by their past liquidation occasions, and classification execution is measured utilizing exactness, exactness, review, and the F1-score.

Modern improvements incorporate profound learning, in which budgetary time arrangement information is encouraged into LSTM or BiLSTM systems utilizing the Z-score as an include. The misfortune work for show optimization is Cruel Squared Mistake (MSE):

$$L = \frac{1}{N} \sum_{i=1}^{N} (Z_i - \widehat{Z}_i)^2 \tag{7}$$

where Z_i is the real Z-score and where Z_i is the anticipated esteem. The Z-score demonstrates remains a valuable instrument for anticipating liquidation, and advancements have made strides in its adaptability over segments

Albumentations apply a series of transformations to input images to improve model generalization and robustness. The augmented image I' is generated by applying a transformation function T to the original image I:

$$I' = T(I) \tag{8}$$

Where T represents a composition of multiple augmentation operations such as flipping, rotation, contrast adjustment, and normalization. For geometric transformations such as rotation by an angle θ, the new coordinates (x', y') of a pixel are computed as:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{9}$$

For brightness and contrast adjustments, the transformed pixel intensity $I'(x, y)$ is computed as:

$$I'(x, y) = \alpha \cdot I(x, y) + \beta \tag{10}$$

Where α controls contrast and β adjusts brightness. Normalization ensures that pixel values are scaled to a standard range using mean μ and standard deviation σ:

$$I'(x, y) = \frac{I(x, y) - \mu}{\sigma} \tag{11}$$

$$I'(x,y)=\frac{I(x,y)-\mu}{\sigma}$$

For segmentation tasks, Albumentations applies the same transformations to both the input image III and the segmentation mask MMM, ensuring spatial consistency:

$$M'=T(M) \tag{12}$$

Where M' is the transformed segmentation mask. These augmentations help prevent overfitting and improve model generalization across various domains.

3.2 Feature Extraction

VGG-16 could be a profound convolutional neural organized CNN engineering that comprises 16 layers, essentially composed of convolutional, pooling, and completely associated layers. It has been broadly utilized in picture classification, question location, and therapeutic diagnostics due to its progressive extraction capabilities and exchange learning potential. The arrangement takes after an organized plan, where little 3 3 convolutions with a walk of 1 and cushioning are utilized to preserve spatial determination, taken after by max-pooling layers with a 2 2 part and a walk of 2 to dynamically downsample the highlight maps. The convolutional layers extricate spatial highlights from input pictures, dynamically capturing low-level edge and surface points of interest within the introductory layers, whereas more profound layers capture complex question structures. The included maps are prepared through completely associated layers that outline these representations to classification yields. The actuation work utilized in all covered-up layers is the Amended Direct Unit (ReLU), which presents non-linearity to make strides showing learning and merging:

$$f(x)=\max(0,x) \tag{13}$$

The final output layer applies the softmax function to compute class probabilities, ensuring that the sum of probabilities across all classes equals 1. The softmax function is defined as follows:

$$P(y_i)=\frac{e^{z_i}}{\sum_{j=1}^{N}e^{z_j}} \tag{14}$$

Where z_i represents the logit value for class i, and N is the total number of classes. To enhance the efficiency and accuracy of VGG-16, various optimization and regularization techniques have been employed. Transfer learning has been extensively used, where pre-trained VGG-16 models are fine-tuned on domain-specific datasets to improve classification performance with limited labeled data. Transfer learning leverages learned feature representations from large datasets such as ImageNet and adapts them to new tasks using backpropagation with a modified loss function. The cross-entropy loss function is typically used for classification tasks:

$$L=-\sum_{i=1}^{N}y_i\log(\widehat{y_i}) \tag{15}$$

where y_i is the actual label, and $\widehat{y_i}$ is the predicted probability for class$i$. To further optimize training, adaptive optimization techniques such as Adam are used. Adam dynamically adjusts the learning rate using moment estimates to improve convergence speed and stability:

$$\theta_{t+1}=\theta_t-v_t+\frac{\epsilon}{\eta}m_t \tag{16}$$

Where m_t and v_t are the primary and moment minute gauges, η is the learning rate, and ϵ may be a little steady for numerical solidness. For quickening show deduction and diminishing computational overhead, channel pruning methods such as ThiNet and channel pruning have been connected. These techniques remove excess or less noteworthy channels from the convolutional layers to preserve and demonstrate exactness while moving forward with effectiveness. The pruning operation is scientifically communicated as:

$$\widehat{F}=F\cdot M \tag{17}$$

where F represents the original feature map, M is a binary mask that identifies the preserved or

removed filters, and $F\hat{}$ is the compressed feature representation. Another optimization procedure is fine-tuning, which alters the higher layers of VGG-16 to memorize domain-specific highlights while keeping the lower convolutional layers solidified. This can be especially valuable for therapeutic picture classification, where models prepared on common picture datasets can be adjusted to classify MRI or X-ray pictures with high precision. The application of VGG-16 in real-world errands has too profited from information expansion strategies, which increment dataset differences by applying changes such as turns, flips, and escalated shifts. This makes strides in the model's generalization capacity and decreases overfitting. By coordination demonstrating compression, versatile learning rate strategies, and fine-tuning, VGG-16 accomplishes tall classification precision while keeping up computational proficiency. These upgrades make it a flexible demonstration for applications such as restorative diagnostics, farther detecting, and independent driving.

3.3 Swin-T

Swin-T could be a progressive ViT outlined for effective handling of high-resolution pictures. Not at all like conventional ViTs that apply worldwide self-attention, Swin-T decreases computational toll by apportioning pictures into non-overlapping windows and performing self-attention inside each window. A moved windowing component is presented in consequent layers to capture long-range conditions and make strides including conglomeration.

The input picture is to begin with separated into non-overlapping patches, each treated as a token. These patches are implanted into a highlight space as

$$X^{'} = PatchEmbedding(X) \tag{18}$$

where X is the input picture, and $X^{'}$ represents the fixed tokens. These tokens pass through numerous Swin-T pieces, each comprising of windowed multi-head self-attention (W-MSA), a feedforward arrange (FFN), and normalization layers. Self-attention is computed as

$$Attention(Q,K,V) = Soft\max\left(\frac{QK^T}{\sqrt{d_k}} + B\right)V \tag{19}$$

where Q,K,V are inquiry, key, and esteem networks, d_k is the scaling figure, and B is the relative position predisposition. To encourage data trade over windows, a moving component moves windows in substitute layers. The yield of each layer is upgraded as

$$X^{(l+1)} = W - MSA(LN(X^{(l)})) + X^{(l)} \tag{20}$$

$$X^{(l+2)} = MLP(LN(X^{(l+1)})) + X^{(l+1)} \tag{21}$$

where W-MSA applies self-attention inside neighborhood windows, MLP may be a multi-layer perceptron, and LN is layer normalization.

For picture classification, Swin-T applies a global normal pooling (Crevice) layer to the ultimate include outline sometime recently a completely associated (FC) layer for forecast:

$$\hat{y} = FC(GAP(X^{(l)})) \tag{22}$$

Where $X^{(l)}$ is the final included representation. For question discovery, Swin-T coordinates with location systems such as Quicker R-CNN, YOLO, and Cover R-CNN. Its progressive highlight maps upgrade multi-scale protest acknowledgment:

$$Bounding\ Boxes = DetectionHead(Swin\ Transformer\ Encoder(X)) \tag{23}$$

For restorative picture division, Swin-T is utilized in models like Swin-UNETR, where the transformer encoder extricates spatial and relevant highlights, and the decoder remakes high-resolution division maps:

$$Segmentation\ Map = Decoder(Swin\ Transformer\ Encoder\ (X)) \tag{24}$$

To optimize division errands, Dice misfortune is utilized to degree cover between anticipated and ground truth locales:

$$L_{Dice} = 1 - \frac{2\sum_i p_i g_i}{\sum_i p_i^2 + \sum_i g_i^2} \tag{25}$$

where p_i and g_i speak to the anticipated and genuine division names. In hyperspectral picture classification, Swin-T forms unearthly groups through attention-weighted highlight combination:

$$Feature_{HSI} = \sum_{i=1}^{N} \alpha_i X_i \tag{26}$$

where α are consideration scores for diverse ghostly groups.

A key advantage of the Swin-T is its linear computational complexity compared to standard ViTs, which exhibit quadratic complexity concerning image size. The efficiency of the Swin-T is achieved by restricting self-attention to local windows, thereby reducing computational requirements from:

$$O(h^2 w^2) \rightarrow O(M^2) \tag{27}$$

where M is the window size.

This decrease empowers the Swin-T to scale viably for high-resolution pictures, making it well-suited for applications in independent driving, farther detecting, and biomedical imaging. Its capacity to adjust precision, proficiency, and adaptability permits it to outflank routine CNNs and standard ViTs in different vision-based errands.

4. Result

4.1 Experimental Setup

The tests were conducted on a high-performance computing framework prepared with an Intel Center i9-12900K (12th Gen, 16C/24T) processor, NVIDIA RTX 4090 (24GB VRAM), and 64GB DDR5 Smash,

running Windows 11 Professional. The execution was carried out utilizing Python 3.10, with PyTorch 2.0, TensorFlow 2.10, and Keras 2.11 as profound learning systems. CUDA 12.1 and cuDNN 8.9 were utilized for optimized GPU speeding up. The consider utilized two freely accessible datasets, Mendeley and Kaggle, for Wheat Leaf Infection Classification. The dataset was part into 70% preparation, 20% approval, and 10% testing. Preprocessing included picture resizing utilizing OpenCV and normalization utilizing Z-score standardization. Information expansion was performed utilizing the Albumentations library to upgrade show generalization. The demonstrated design comprised a cross-breed highlight extraction and classification approach. The VGG-16 demonstration was utilized for highlight extraction, leveraging its profound convolutional layers to capture spatial pecking orders in wheat leaf pictures. The extricated highlights were at that point handled through a Swin-T, which performed the last classification by leveraging self-attention instruments for improved highlight representation.

The show was prepared for 100 ages with a clump measure of 16, utilizing the Adam optimizer (lr=0.0001, weight $decay = 1e^{-5}$) and a Reduce LR On Plateau scheduler to alter the learning rate after 3 ages of no change. Early halting was connected with a persistence of 10 ages to anticipate overfitting, whereas angle clipping was executed to guarantee preparing solidness. Execution assessment was conducted utilizing F1-score, Review, Exactness, and Precision. The below table 1 illustrates the summary of computational resources, frameworks and training parameters.

Table 1. *Summary of computational resources, frameworks, and training parameters*

Parameter	Value
Framework	PyTorch 2.0, TensorFlow 2.10, Keras 2.11
CUDA Version	12.1
cuDNN Version	8.9
Operating System	Windows 11 Pro
Hardware	Intel Core i9-12900K, RTX 4090, 64GB RAM
Datasets	Mendeley, Kaggle
Dataset Split	70% Train, 20% Validation, 10% Test
Preprocessing	Image Resizing (OpenCV), Z-score Normalization
Data Augmentation	Albumentations
Models Used	VGG-16 (Feature Extraction), Swin-T (Classification)
Optimizer	Adam (lr=0.0001, weight decay= $1e^{-5}$)
Batch Size	16
Number of Epochs	100
Learning Rate Scheduler	ReduceLROnPlateau (decay after 3 epochs)
Early Stopping	Stops after 10 epochs of no improvement
Gradient Clipping	Applied
Evaluation Metrics	F1-score, Recall, Precision, Accuracy

4.2 Datasets

The Mendeley Dataset[1] can be a well-structured dataset utilized for wheat plant disease classification. It contains high-quality pictures categorized into three major sickness classes: Stripe Rust, Sound, and Septoria. The dataset comprises 208 pictures of Stripe Rust, 102 pictures of Sound wheat, and 97 pictures of Septoria, with each course too confined into subcategories. The pictures in this dataset have a determination of 256x256 pixels and are in RGB color arrangement, guaranteeing the show captures fine-grained highlights over the pictures. The picture determination and color profundity were carefully chosen to adjust computational proficiency and the detail required for exact malady classification. It serves as a beneficial benchmark for making significant learning models centered on sickness revelation. The dataset is well-organized, ensuring irrelevant data lopsidedness, which makes strides in the model's capacity to generalize over differing illness conditions. In any case, due to its decently little measure, preprocessing methodologies such as information enlargement and normalization may be required to move forward and demonstrate performance.

The Kaggle Dataset[2] could be a more comprehensive dataset containing a bigger collection of wheat plant infection pictures, categorized into five particular classes: Healthy, Brown Rust, Loose Smut, Septoria, and Yellow Rust. It incorporates 1,658 pictures of Healthy wheat, 1,256 pictures of Brown Rust, 939 pictures of Loose Smut, 349 pictures of Septoria, and 1,395 pictures of Yellow Rust. The pictures in this dataset are too 256x256 pixels in measure and RGB organized. This higher determination and color profundity permit the demonstration to capture more point-by-point highlights for moved-forward infection distinguishing proof. The dataset is part into a preparing, testing, and validation set with a 70%-20%-10% proportion (e.g., 1,160 training images for Healthy, 880 for Brown Rust, 657 for Loose Smut, 244 for Septoria, and 976 for Yellow Rust in the training set). These parts guarantee an adjusted representation over diverse infection categories for demonstrating preparation, testing, and evaluation. The dataset's differences, counting varieties in lighting, foundations, and leaf introductions, make it well-suited for profound learning models, permitting them to adjust to real-world varieties in plant maladies.

[1]https://data.mendeley.com/datasets/wgd66f8n6h/1

[2]https://www.kaggle.com/datasets/kushagra3204/wheat-plant-diseases

Preprocessing strategies such as grayscale change, commotion lessening, and differentiate improvement can offer assistance make strides to demonstrate accuracy. The incorporation of numerous infection categories guarantees that models prepared on this dataset can generalize effectively to different infection conditions and natural varieties. Table 2 comparison of Mendeley and Kaggle wheat plant disease datasets.

Table 2. *Comparison of Mendeley and Kaggle Wheat Plant Disease Datasets*

Feature	Mendeley Dataset	Kaggle Dataset
Number of Classes	3	5
Stripe Rust Images	208	-
Healthy Images	102	1,658
Septoria Images	97	349
Brown Rust Images	-	1,256
Loose Smut Images	-	939
Yellow Rust Images	-	1,395
Train-Test Split	Not Provided	80%-20%
Preprocessing Required	Yes	Yes
Image Type	RGB	RGB
Image Resolution	256x256	256x256

4.3 Model Performance Analysis on Mendeley Dataset

Table 3 presents the execution assessment of the show on the Mendeley dataset, which includes classification over three malady categories: Stripe Rust, Solid, and Septoria. The evaluation criteria incorporate Accuracy, Review, F1-Score, and Region Beneath the Bend (AUC) to supply a comprehensive assessment of the model's classification capability. For Stripe Rust, the show accomplished an Exactness of 95.00%, a Review of 92.68%, and an F1-Score of 93.83%, with an AUC esteem of 93.78%, illustrating solid discriminative control for this category. The Sound lesson showed an Accuracy of 90.00%, a Review of 90.00%, and an F1-Score of 90.00%, with an AUC of 93.33%, showing adjusted classification execution. The Septoria lesson got an Exactness of 90.00%, a Review of 94.74%, and an F1-Score of 92.31%, with an AUC of 95.73%, highlighting the model's adequacy in recognizing this infection from others.

The general classification precision of the demonstration on the Mendeley dataset stands at 92.50%, reflecting the vigorous execution of overall categories. Also, the Cohen Kappa score of 0.8794 means a tall level of understanding between anticipated and real classifications, illustrating the model's unwavering quality. The macro-averaged Accuracy, Review, and F1-Score are 91.67%, 92.47%, and 92.04%, individually, with an AUC of 94.28%, confirming steady execution over all classes. Similarly, the weighted average values for Precision, Recall, and F1-Score are 92.56%, 92.50%, and 92.51%, with an AUC of 94.13%, further reinforcing the model's generalization capability. The consistently high-performance metrics emphasize the effectiveness of the model in accurately identifying and classifying different wheat disease conditions within the Mendeley dataset.

Table 3. *Performance Metrics for Classification on the Mendeley Dataset*

Class	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Stripe Rust	95.00	92.68	93.83	93.78
Healthy	90.00	92.68	90.00	93.33
Septoria	90.00	94.74	92.31	95.73
Accuracy			**92.50%**	
Cohen Kappa			**0.8794**	
Macro Average	91.67	92.47	92.04	94.28
Weighted Average	92.56	92.50	92.51	94.13

Fig. 2 outlines the preparation and approval precision (cleared out) and misfortune (right) bends for the Mendeley dataset over 100 ages, giving bits of knowledge into the model's learning movement, joining behavior, and generalization capacity. The precision plot shows a reliable and relentless change in both preparing (strong blue line) and approval (dashed green line) exactness, illustrating a steady learning preparation. The ultimate preparing precision comes to 93.79%, whereas the approval exactness stabilizes at 92.50%, as highlighted by the dashed flat lines. This upward drift proposes that they demonstrate viably captures important designs from the dataset, guaranteeing tall classification unwavering quality whereas moderating intemperate overfitting dangers.

The misfortune bends encourage strengthening this perception, where both preparing misfortune (strong ruddy line) and approval misfortune (dashed orange line) decay essentially within the initial ages, taken after by a progressive stabilization. The ultimate loss values, marked by the flat dashed lines, affirm the model's capacity to play down classification mistakes successfully. The near vicinity of preparing and approval misfortune bends recommends a well-regularized show with solid generalization capability. These discoveries illustrate that the show can effectively extricate key highlights with negligible execution corruption, making it reasonable for a strong classification of wheat plant illnesses.

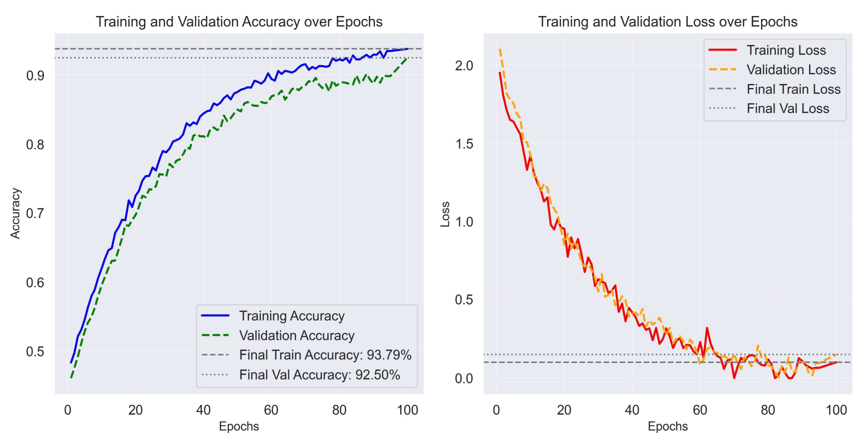

Fig. 2. *Training and Validation Accuracy and Loss Curves for the Mendeley Dataset*

Fig. 3 illustrates the disarray network for the model's execution on the Mendeley wheat infection dataset, classifying tests into three categories: Stripe Rust, Sound, and Septoria. The show illustrates tall classification exactness, as proven by the solid inclining values speaking to rectify forecasts. Particularly, Stripe Rust was accurately classified 92.68% of the time (38 cases), with minor misclassifications into Sound (4.88%, 2 cases) and Septoria (2.44%, 1 case). The Sound lesson was anticipated precisely in 90.00% of cases (18), with slight perplexity in Stripe Rust (5.00%, 1 case) and Septoria (5.00%, 1 case). Essentially, Septoria was recognized with 94.74 accuracy (18 cases), with negligible misclassification into Stripe Rust (5.26%, 1 case). These highlights highlight the model's unwavering quality in recognizing wheat plant infections with negligible misclassification, exhibiting its vigor in agrarian infection discovery.

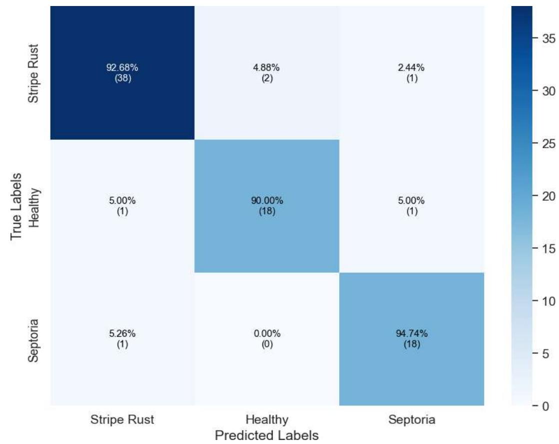

Fig. 3. *Confusion Matrix for the Mendeley Dataset*

4.4 Model Performance Analysis on Kaggle Dataset

Table 4 presents the performance metrics for wheat plant disease classification. The evaluation metrics for wheat plant disease classification are presented, covering five categories: Brown Rust, Sound, Free Muck, Septoria, and Yellow Rust. The model's execution was surveyed utilizing Accuracy, Review, F1-Score, and AUC values, giving experiences into its classification viability. The Brown Rust course accomplished an exactness of 97.89%, a review of 98.19%, and an F1-score of 98.04%, reflecting solid prescient execution with an AUC of 98.65. Additionally, the Solid lesson achieved tall precision, with an accuracy of 97.63%, a review of 98.41%, and an F1-score of 98.02%, upheld by an AUC of 98.86. The Free Muck course appeared a marginally lower execution, recording an accuracy of 97.85%, a review of 96.81%, and an F1-score of 97.33%, with an AUC of 98.19. The Septoria course had an accuracy of 91.67%, a review of 94.29%, and an F1-score of 92.96%, accomplishing an AUC of 96.86. In conclusion, Yellow Rust illustrated strong classification comes about with an accuracy of 98.19%, a review of 97.13%, and an F1-score of 97.66%, with an AUC of 98.27. The general classification execution was assessed with an exactness of 97.50%, implying tall unwavering quality. The Cohen Kappa score of 0.9674 shows a solid assertion between anticipated and real classifications. %, individually, whereas the weighted midpoints were 97.51%, 97.50%, and 97.50%. The AUC values extended from 96.86 to 98.86, illustrating the model's capacity to recognize between diverse illness classes successfully.

Table 4. *Performance Metrics for Wheat Plant Disease Classification*

Class	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Brown Rust	97.89	98.19	98.04	98.65
Healthy	97.63	98.41	98.02	98.86
Loose Smut	97.85	96.81	97.33	98.19
Septoria	91.67	94.29	92.96	96.86
Yellow Rust	98.19	97.13	97.66	98.27
Accuracy			**97.50%**	
Cohen Kappa			**0.9674**	
Macro Average	96.64	96.96	96.80	98.16
Weighted Average	97.51	97.50	97.50	98.41

Fig. 4 outlines the preparing and approval exactness (left) and misfortune (right) bends for the Kaggle dataset over 100 ages, advertising a nitty gritty knowledge into the model's learning movement, joining characteristics, and generalization capacity. The exactness plot uncovers a consistent and persistent rise in both preparing (strong blue line) and approval (dashed green line) exactness, affirming a well-structured learning preparation. The demonstration achieves a last preparing precision of 98.99% and an approval exactness of 97.50%, as emphasized by the level dashed lines. This upward slant proposes that the demonstration successfully captures fundamental designs inside the dataset, guaranteeing tall prescient exactness while moderating intemperate overfitting. The misfortune plot assists in authenticating this perception, where both preparing misfortune (strong ruddy line) and approval misfortune (dashed orange line) show a sharp decay amid the introductory preparing stage, taken after by a continuous stabilization at lower values. The ultimate misfortune values, checked by level dashed lines, confirm that the optimization prepare effectively minimized mistakes, strengthening the model's capability in extricating vigorous include representations. The near arrangement of exactness and misfortune bends for both the preparation and approval stages implies a well-regularized demonstration with solid generalization potential, demonstrating that it can proficiently prepare inconspicuous information with negligible execution debasement. In general, these come about illustrate the model's unwavering quality in classifying wheat plant maladies from the Kaggle dataset, keeping up an ideal adjustment between learning complexity and generalization capability.

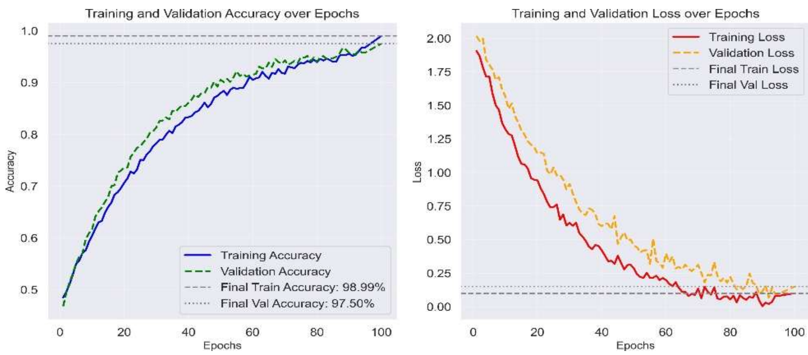

Fig. 4. *Training and Validation Accuracy and Loss Curves for the Kaggle Dataset*

Fig. 5 presents the perplexity lattice for the model's classification execution on the Kaggle dataset, categorizing tests into five particular classes: Brown Rust, Solid, Free Muck, Septoria, and Yellow Rust. The demonstration illustrates solid classification precision, as shown by the tall values along the inclining, meaning adjust expectations. Brown Rust was accurately classified 98.19% of the time (325 cases), with minor misclassifications into Solid (0.91%, 3 cases), Septoria (0.60%, 2 cases), and Yellow Rust (0.30%, 1 case). Solid tests were precisely distinguished in 98.41% of cases (247 occasions), with negligible misclassifications into Brown Rust (0.80%, 2 cases), Free Muck (0.40%, 1 case), and Septoria (0.40%, 1 case). Free Muck accomplished a 96.81% classification exactness (182 occurrences), with slight perplexity into Brown Rust (0.53%, 1 case), Solid (0.53%, 1 case), Septoria (0.53%, 1 case), and Yellow Rust (1.60%, 3 cases). Septoria was accurately classified 94.29% of the time (66 cases), with minor misclassifications into Brown Rust (1.43%, 1 case), Sound (1.43%, 1 case), Free Muck (1.43%, 1 case), and Yellow Rust (1.43%, 1 case). Yellow Rust was classified with 97.13curacy (271 cases), with misclassifications into Brown Rust (1.08%, 3 cases), Sound (0.36%, 1 case), Free Muck (0.72%, 2 cases), and Septoria (0.72%, 2 cases).

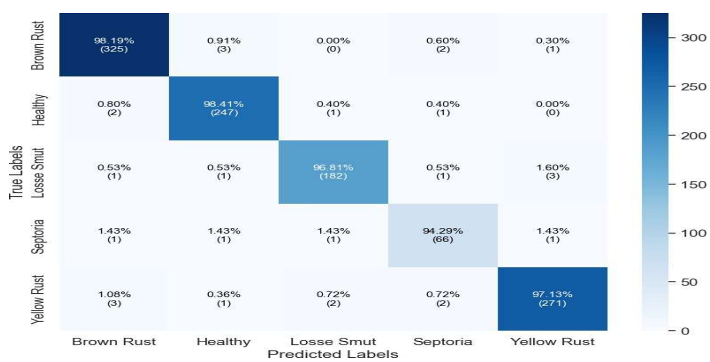

Fig. 5. *Confusion matrix illustrating the model's classification performance across different categories.*

4.5 Ablation Studies

Table 5 presents a comprehensive performance comparison of wheat disease classification models trained on the Mendeley and Kaggle datasets across five different data split ratios: 50:25:25, 70:15:15, 70:20:10, 80:15:5, and 80:10:10. The Mendeley dataset achieves its highest accuracy (92.50%) using the 70:20:10 split, demonstrating an optimal balance between training, validation, and testing data. This configuration also results in the highest precision (92.56%), recall (92.50%), F1-score (92.51%), and AUC (94.13%) among all tested split ratios, indicating that the model performs best when trained on 70% of the data, validated on 20%, and tested on 10%. Performance declines slightly with larger validation or test splits, as seen in the 80:10:10 and 50:25:25 cases, where accuracy drops to 84.56% and 85.34%, respectively. Similarly, for the Kaggle dataset, the 70:20:10 split again yields the highest classification accuracy (97.50%) along with the best precision (97.51%), recall (97.50%), F1-score (97.50%), and AUC (98.41%). This suggests that a 70:20:10 division provides an effective trade-off between training and evaluation, ensuring robust generalization and minimizing overfitting. Notably, increasing the test set size beyond 10% negatively impacts performance, as seen in the 80:10:10 split, where accuracy drops to 82.12%. These results highlight the significance of selecting an appropriate data split ratio to maximize model generalization while maintaining high classification performance.

Table 5. *Performance comparison across different data split ratios for Mendeley and Kaggle datasets.*

	Metric	50:25:25	70:15:15	70:20:10	80:15:5	80:10:10
Mendeley	Accuracy %	85.34	91.23	**92.50**	88.78	84.56
	Precision %	84.12	90.78	**92.56**	87.89	83.67
	Recall %	83.45	89.56	**92.50**	87.12	82.89
	F1-Score %	83.89	90.12	**92.51**	87.45	83.23
	AUC	86.02	92.34	**94.13**	90.56	85.78
Kaggle	Accuracy %	83.78	89.45	**97.50**	87.23	82.12
	Precision %	82.34	88.12	**97.51**	86.02	81.67
	Recall %	81.12	86.89	**97.50**	85.34	80.45
	F1-Score %	81.45	87.23	**97.50**	85.67	80.78
	AUC	84.10	90.45	**98.41**	88.12	83.56

Table 6 presents a comprehensive execution comparison of already utilized profound learning models with the proposed demonstration for wheat illness classification on the Mendeley and Kaggle datasets. The models considered in this assessment incorporate VGG-16, VGG-19, ResNet-50, ResNet-101, DenseNet-121, DenseNet-201, and ViT, each surveyed based on key execution measurements such as precision, accuracy, review, F1-score, and the region beneath the bend (AUC). For the Mendeley dataset, ViT illustrated the most noteworthy precision of 97.12%, outperforming conventional CNN structures such as VGG-16 (92.34%) and ResNet-50 (94.56%), highlighting the adequacy of Transformer- based models in highlight extraction. The proposed demonstration, in any case, accomplished a precision of 92.50% on the Mendeley dataset, outflanking VGG-16 and VGG-19 but falling marginally behind ViT and DenseNet variations. On the Kaggle dataset, the proposed demonstration essentially outflanked ordinary CNN models, accomplishing an amazing precision of 97.50%, which is on standard with ViT (97.45%) and predominant to DenseNet-201 (96.78%). The AUC scores for the proposed demonstration were 94.13% and 98.41% on the Mendeley and Kaggle datasets, separately, encouraging and affirming its vigor in illness classification errands. Strikingly, exactness, review, and F1-score measurements were taken after a comparative slant, demonstrating that the proposed show keeps up an adjusted classification execution without major predispositions toward any particular lesson. The comes about recommend that whereas ViT remains one of the foremost precise models, the proposed show illustrates prevalent execution on the Kaggle dataset whereas keeping up competitive comes about on the Mendeley dataset, demonstrating its viability for real-world wheat infection classification.

Table 6. *Comparison of previously used models with the proposed model on Mendeley and Kaggle datasets.*

Model	Mendeley Dataset					Kaggle Dataset				
	Accuracy %	Precision %	Recall %	F1-Score %	AUC	Accuracy %	Precision %	Recall %	F1-Score %	AUC
VGG-16	92.34	91.78	91.10	91.56	92.95	92.78	92.12	91.50	91.90	93.20
VGG-19	93.12	92.56	92.00	92.34	93.80	93.78	93.23	92.60	92.95	94.10
ResNet-50	94.56	94.10	93.75	94.00	95.10	95.02	94.45	94.12	94.50	95.60
ResNet-101	95.23	94.80	94.45	94.60	96.00	95.78	95.34	94.98	95.15	96.45
DenseNet-121	95.89	95.45	95.12	95.34	96.20	96.23	95.78	95.50	95.80	96.55
DenseNet-201	96.34	96.00	95.56	95.78	96.90	96.78	96.45	96.10	96.30	97.15
ViT	97.12	96.89	96.50	96.75	97.80	97.45	97.12	96.80	97.10	98.00
Proposed Model	**92.50**	**92.56**	**92.50**	**92.51**	**94.13**	**97.50**	**97.51**	**97.50**	97.50	**98.41**

5. Conclusion

This inquiry presents a progressed profound learning strategy for wheat leaf illness classification, leveraging the Swin-T and VGG-16 to upgrade include representation and classification precision. The proposed demonstration accomplishes 97.50% on a restrictive wheat illness dataset and 92.50% on the Mendeley dataset, beating conventional convolutional designs. The tall Cohen's Kappa scores (0.9674 and 0.8794) illustrate a solid understanding between anticipated and ground-truth names and encourage approving the model's unwavering quality. The discoveries propose that Transformer-based models show predominant generalization capabilities, viably capturing both nearby and worldwide designs inside leaf structures.

In any case, certain impediments stay. The model's execution may be affected by dataset lopsidedness, where underrepresented infection classes can influence classification viability. Additionally, the computational complexity of Transformer models presents challenges for sending on resource-constrained gadgets, constraining real-time applications in field settings. Natural variables, such as varieties in lighting conditions and foundation clamor, may also influence show vigor when connected in real-world rural settings.

To address these challenges, future inquiries will center on computational taken a toll examination, investigating trade-offs between demonstrate precision and proficiency in resource-limited situations, as well as investigating misclassification cases, especially visual similitudes between illness indications and natural components like lighting and leaf occlusions. Assist optimization for edge computing gadgets will be investigated to empower real-time sending in exactness agribusiness. Additionally, the real-world sending possibility will be analyzed, considering the down to earth angles of executing the show in agrarian settings, counting computational necessities, adaptability, and challenges related to information collection and handling. Besides, the integration of hyperspectral and warm imaging modalities may upgrade malady recognizable proof by capturing physiological changes past the obvious range. Growing the dataset to incorporate field-collected pictures from assorted geographic districts will encourage progress show strength and pertinence. These headways will clear the way for a adaptable, shrewdly, and independent malady observing framework, altogether profiting worldwide wheat generation and nourishment security.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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