International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Conference Proceedings: Volume: 05 ACME – 2026 DOI: 10.55041/ISJEM.ACME002
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Multi Stage Neural Network Based Ensemble Learning Approach for Wheat Leaf Disease Classification

Mamanduru Sunil
M-Tech, Department .Of Computer Scince And Engineering,
Vemu Institute Of Technology,
P.Kothakota,Chittoor District, Andhra Pradesh-517112,India
Email Id: Mamandurusunil2000@Gmail.Com

Mr.Dharmaiahvari prasad
Assistant professor, M.Tech,Dept of CSE,
Vemu institute of Technology ,p.kothakota.
Email Id: dprasadnaresh@gmail.com

Abstract: The proposed automated system in the paper I. relies on the notion of deep learning and the proposed functionality is to identify the diseases of the wheat plants with the help of Wheat Plant Diseases dataset that could be downloaded without cost on Kaggle. The paper proves the effectiveness of the test and the analysis of the work of one of the most successful representatives of the convolutional neural network (CNN) the ResNet50, DenseNet201, VGG19, NASNetLarge, Swin Transformer, and Vision Transformers (ViT). These models they are trained and fitted on are used to classify the diseases of wheat plants Aphid, Black Rust, Blast, Fusarium Head Blight, Yellow Rust etc. The evaluation of such models is also done in terms of accuracy and precision of models, recall and F1-score of models. The obtained results are evidence that DenseNet201 and Swin Transformer were the only networks that achieved the highest accuracy of 93 and the other networks possessed the following determinacy (ResNet50 (75), VGG19 (91), ViT (90), NASNetLarge (88) and CNN (90)). The paper shall make commentary on the future of deep learning as applied in precision agriculture which is a reliable and feasible mechanism in the detection of diseases in wheat plants at the appropriate time. Not only will this go a long way in helping the farmers and other agricultural professionals to reduce the losses of crops but also to greater awareness on yield and further crop protection.

Keywords: Deep Learning, CNN, ResNet50, DenseNet201, VGG19, Nasnetlarge, MobileNetV2, Vision transformers, Swin transformer, Plant pathology, Image classification**,** *Precision agriculture, agricultural AI, Transfer learning.*

INTRODUCTION

Some of these crops include wheat that is one of the greatest crops in the world, given the fact that it forms a big portion of human diet and it has great economic value to the world. Nonetheless, plants have a number of disease conditions which do not only pose a threat to production of wheat, but failure to identify the disease conditions in a timely manner may translate to colossal wastage of harvests. Previously, such diseases were supposed to be diagnosed manually by the agricultural professionals which implied it was a time consuming exercise and endangered by human errors. Therefore, the automated disease detecting systems are already matters of great concern given that it is in a position to provide solutions that are not only faster than the rest, but also more accurate.

Even the work of the deep learning, in the specified scenario, the convolutional neural networks (CNNs), which are the latest trends in the area, have altered even the very activities of the image classification, one of which is the phenomenon the disease recognition of the plant interrelated. The CNNs have the ability to produce automatic properties of the pictures, which are most suitable as far as the task of identifying the disease in the agricultural industry is involved. According to the article, the most recent CNNs such as ResNet50, DenseNet201, VGG19, NASNetLarge, Swin Transformer, and Vision Transformers (ViT) have been applied in classifying the diseases of wheat plants. We will also perform the comparison and contrast performance of these models against each other in the perspectives of such central measures as accuracy, precision, recall, and F1-score.

The proposed study will also be directed towards the creation of a viable disease detection model when deep learning on wheat is available which will provide to the farmers and other experts involved in the agriculture industry a viable mechanism of detecting the disease at the earliest stage to prevent losses and crops harvesting.

A. Objective of The Study:

The concept of the presented work was to develop the efficient system of deep learning, which could be mechanized and used to detect the diseases of wheat plants in the photo dataset. The paper will make a comparison and contrast of the performance of some state of the art convolutional neural network (CNN) architecture search on the most successful architecture will be adopted in the determination of the diseases. The system will be identified as the case will classify the images of the wheat plants into the different varieties of the diseases like Aphid, Black Rust, Blast, Fusarium Head Blight among others and Yellow Rust. The performance, accuracy, preciseness, recall and F1-score of the implementation will be useful in quantifying the same. It would have a desire to show an effective and realistic self-help measure that would help the farmers and the farm animals in diagnosing the disease at an earlier stage hence, take the necessary step to save the loss of crops at an early stage hence stabilizing the production of the wheat crop and its sustainability.

B. Problem Statement:

The wheat crops are vulnerable to myriads of diseases and therefore, there are tremendous opportunities of diseases that will greatly affect the growth and crop production a major threat to the world food security. To ensure that the devastating effect of the crops is minimized and to realize sustainable crop production, the severity of the diseases and their early appearance should be checked. However, the programmed diagnostic procedures of pervasive disease which is supported by physical inspection of physicians is a time and error-prone procedure that is most likely to generate the latter. It is not scalable and practicable as the process of wheat production is a mass process. Therefore, there is an acute necessity to possess a computerized precise and consistent system that would recognize and cluster the wheat ailments, on the timely basis with the help of image data. It has turned out to possess an infinite number of possibilities that can be offered by the deep-learning methodology and, more precisely, convolutional neural networks (CNNs) to eliminate this issue, but whether the most efficient model can be offered to detect the diseases in wheat or not is also a controversial issue.

II. RELATED WORKS

The second problem is also among the most commonly spread in the area of precision farming and a major scientific priority of smart farming and plant pathology and is the adequate and timely identification and classification. It contains twelve major articles in IEEE and others that represent perfection and prospective methods to identify and categorize the wheat leaf/plant disease. As may be noted the development of research in this field is not just transitioned into the models of hybrid architecture designing, but also lightweight ones in order to deploy in the models of edge/transformer-based, this has contributed to the accuracy of operational capacity to work with multifaceted backgrounds and deploy on the spot to the requirements of agriculture.

The existing research on detection of wheat diseases with the help of deep convolutional neural networks (CNNs) is aimed at the fulfilment of the machine learning as the means of diagnosis and identification of diseases in wheat. A CNN model was created in the former, and it was considered to analyze the picture of wheat plants, the accuracy of which was 95% and was significantly higher than the classical image recognition. The specified methodology utilizes the preprocessing algorithms that involve the data augmentation and normalization to the object to improve the model behaviour and make it resistant to the changes in the environment [1]. On the same note, the second article can expound on the use of CNNs in detection of diseases such as rust and blight of wheat with the model achieving an accuracy of 92 percent. The opportunity has been linked with the combination of these deep learning algorithms and precision farming as stated in the current paper to detect the diseases automatically and in real-time [2].

The study at proposes a model that is known as the integrated deep learning and ensemble learning (IDLF EL) to classify the wheat plant diseases using images, whereby the deep features and multi classifiers are employed to know the performance of the individual classifier that improves the overall accuracy and generalization, as it yields to high accuracy in the process of identifying the disease in the crop e.g. the yellow rust and the brown rust [3]. The CNNs-based lightweight wheat leaf disease classification model and the other pre-trained models (ResNet50, EfficientNet, MobileNet) including image preprocessing, training the model with the optimization of hyperparametric, and evaluation with an unknown dataset, shows the good performance of all the diseases that could be implemented on an embedded platform and be used in a farm [4] [5].

The paper will review the biology and epidemiology of wheat leaf rust by Puccinia triticina, describe how the pathogen infects and spreads on wheat, and comment on the interactions between, on the one side, the host, and, on the other side, the pathogen that establish the disease progression and increase the severity of its manifestations. Wheat leaf rust can induce extreme suffocation of yield and quality of the wheat leaf and the pathogen life cycle and infection can be supreme to breeding and management of the resistant wheat genotypes [6].

The review consists of tendencies in the use of convolutional neural net models and comprises of VGG, EfficientNet, GoogleNet, and ResNet and states that these deep learning models are generally characterized by high quality of accuracy and that problems associated with the diagnosis of plant disease involve the unavailability of larger datasets to achieve this and superior generalization methods [7]. An enhanced hierarchical residual vision vision transformer architecture is a refinement of Vision Transformer and ResNet9 based classifier that predicts leaf diseases at an early stage on datasets up to 51 classes and is much more capable of discovering meaningful discriminative features using fewer trainable parameters and higher classification than other models including InceptionV3 and MobileNetV2 [8].

The explainable AI CNN model was created to identify and explain the diseases of wheat crop and used the field images accordingly to generate reliable predictive models and faster convergence besides 100 percent of classification in the chosen cases besides other related features that made the predictions to be considered to be appropriately adapted to the field version of agriculture [9]. It was shown that a multimodal data fusion system was which involved a combination of high resolution images of leaves of wheat and images of environments condition; temperature, humidity and soil moisture, increased ability to identify pests and diseases by 96.5 with a precision of 94.8, 97.2 recall and F1 indicated best ability of visual and environmental images to provide reliable data on the condition of wheat leaves [10]. The MobileNet V3 outperformed the other CNNs; MobileNetV3, DenseNet121, ResNet50 and EfficientNetB0 on the classification of the most prevalent wheat rust diseases i.e. brown rust, stem rust and yellow rust most of them by a margin of 97.7 out of the rest in a comparative study of the models [11].

The result was an object detection and classification system to detect automated wheat disease between the Global Wheat Head Detection (GWHD) and Large Wheat Disease Classification (LWDC) datasets, which was trained on that of GWHD dataset and obtained a mean average precision (mAP) of between 91% and the learned weights with pre trained on LWDC dataset, when the system was utilized alongside CNN classifiers like VGG19, resulting in a poignant classification accuracy of approximately 95% on such diseases like the Fusarium Head Blight and Loose Smut [12] It offered a high performance wheat disease detection model that relies on position attention block to offer enhanced spatial feature extraction in CNNs and a position attention enhanced ResNet model that was proposed with 96.4 percent classification accuracy and reliability across datasets and object detection of a result in case it is applied in conjunction with other models such as YOLOv3 and YOLOv5 [13].

It presented a deep learning based architecture of plant disease detection that used the WY CN NASNetLarge the model trained on large datasets, including Yellow Rust 19, Corn Disease and Severity (CDS) and PlantVillage and data augmentation, and AdamW optimizer, dropout and mixed precision training to achieve a high classification accuracy of 97.33% and more competitive architectures as ResNet152V2, inceptionresnetv2 and denseNet201 on severity of disease prediction [14]. Two step compressed hybrid model that was learned by denseNet and involutional layer including weight pruning and knowledge distillation to reach high accuracy rates of up to 99.55 and 98.99 of predicting plant diseases on the PaddyLeaf and PlantVillage respectively were used to minimize the computation resource requirements of the network in resource constrained devices whilst maintaining high-accuracy rates of up to 99.55 and 98.99 respectively [15].

As it is stated in the provided body of knowledge, the gaps in management of the provided study are quite broad, primarily, because of the small volume of data utilized and a controlled environment of the experiment, which restricts the access to the factors of the environment and a range of health concerns. There are also no such comparisons of the architectures of various models as ResNet50, ViT, MobileNet V2, EfficientNet and Swin Transformer that are compared, equalized, and trained on the same preprocessing and augmentation, and evaluated, etc. Although positive impressions are also present and combination with ensemble and multi-stage hybrid models (e.g. Faster R-CNN + SVM or multi-CNN

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fusion is tested specifically on publicly available Kaggle-like datasets) are also in place, most of them are not actually tested on publicly available Kaggle-like datasets. Moreover, the deployed models are not capable of offering high-performance on binary and multi-class tasks and the severity tasks and the applications which can be provided to the farmers in real-time and are accessible. The paper fills these gaps by training a multi-phase neural network to make comparisons between the state-of-the-art CNN model and a user trained CNN model. This section of the paper involves the use of transfer learning and fine-tuning and the same preprocessing and augmentation is performed to determine the accuracy, precision, recall and F1-score of each model and eventually the most effective model to classify the disease is reached and utility-based tools are offered so that the farmers can know when to act to save their harvest.

III. PROPOSED SYSTEM

The system developed will be based on the deep learning methods which will enable the system to distinguish between the diseases of the wheat plants automatically as per the convolutional neural networks. The information will be processed and subjected to various advanced models to detect diseases with the assistance of the system that will be constructed on the picture of wheat plants. The models will as well learn to distinguish different diseases in wheat, with the help of image, and this will enable the model to distinguish the diseases on the wheat through a fast and accurate process. The system will alternate the CNN designs by providing the outcomes of the performance that consists of the outcomes of accuracy and precision and the outcomes of recall and F1-score, in order to end the system which provides the best performance. The system will automatically detect the diseases and thus the farmers and agricultural experts are in a position to act instantly in response to the disease and thus minimize the losses incurred by the crop and management of crops improved. We shall seek to develop one of the best solutions to the agricultural sector which will be in place to grow alongside the agricultural requirements to help in the sustenance of the wheat agricultural practice.

It is completely automatic, i.e., the building identifies the diseases of wheat by a user authentication using his/her registered accounts. Once the user has passed through the log-in process, he/she is able to drop the photos of the wheat plants to be examined with reference to the disease. The supported-end functions would be projected to three stages with the initial one being the data collection and followed by the data preprocessing stage and ended by a model creation using different deep learning networks include the ResNet50 and the DenseNet201 and VGG19 and NASNetLarge and CNN and ViT and Swin Transformer. The models are trained and tested to determine the diseases that comprise Aphids and Black Rust and Blast and Fusarium Head Blight and other diseases in terms of performance measurement where the accuracy and the precision and the recall and F1-score is determined. The system forecasts the disease that the farmers and agricultural gurus trace to establish any disease at a certain level with the aim of taking the correct action to lessen the loss of crops and maximize the output of the farming production as presented in Fig. 1.

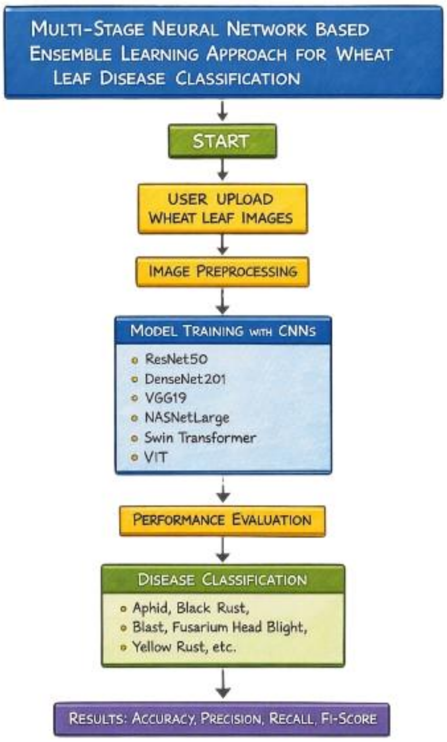

Fig. 1. Project Flow

IV. METHODOLOGY

A. Dataset

Wheat Plant Diseases Dataset has 300 validation samples and 13104 training samples. The photos maintain the explanation of the varying kinds of the disease that are Aphid Black Rust Blast Fusarium Head Blight Yellow Rust and a normal classification. The deep learning models can be trained using training samples and its validation with the help of the validation sample, which is also used to discover the level of the model and its ability to apply the learned ability to handle the situation at hand. An essential data will form part of the

ISSN: 2583-6129
DOI: 10.55041/ISJEM.ACME002

information that will be needed to develop and streamline the convolutional neural networks that will perform effectively in the classification of the diseases of wheat. The balance distributed between the training and the validation data is applied in the gaining of real world application reliability in the model.

B. Data Preprocessing

The process used in preparing the data involves the data of the wheat plant diseases in the form of the training and validation images in the two storage media. The images are then reduced in the number of pixels to 128x128 in the size so that it becomes equal to the models. The validation and the training samples are 300 and 13104 respectively. The pictures were presented with the name of the kind of illness they portray in them as well as some of them having Aphid, Black Rust, Blast and other illness in them. The researchers have used the resizing and normalization data augmentation methods in an effort to enhance better generalization to the models. It comes below batches information stacking, which entails shuffling of the training information to come up with random information during the process of training the models in an attempt to overcome over fitting.

C. Model Training

The other authors used deep learning architecture to identify their wheat disease dataset. The data provided can also be divided into the training and the validation data set whereby the former is utilized when instructing the images in the process of determining the patterns in the images. The training data is subsequently applied to train the various models that comprises of ResNet50 models and the DenseNet201 models and that is trained on the backpropagation and Adam optimization that illustrated the modifications in the loss functions. The validation group is also based on the manner in which the model will be during the training hence good generalization of the model to the unseen data. The effectiveness of the team with respect to life of team project depends on the accuracy of the team and F1-score of the team.

1) DenseNet201:

DenseNet201 serves as a deep convolutional neural network because it connects all its layers through feed-forward links which lead to better feature flow and an efficient decrease of parameter requirements. The model learns complex representations better because it receives input from all previous layers at every layer. The main benefit of DenseNet stems from its implementation of "dense blocks," which allow each layer to combine its output with the incoming signals of following layers.

a) Mathematical Equations: For DenseNet, the output H_l of layer l is defined as:

$$H_l = F(H_{l-1}, \{H_0, H_1, \dots, H_{l-1}\}) \quad (1)$$

where F is the transformation function applied to the concatenated features of all preceding layers.

In DenseNet, the transition between blocks is achieved by:

$$T_l = \text{BatchNorm}(W_l \cdot H_l + b_l) \quad (2)$$

where W_l and b_l are the weights and biases for the transition layer.

2) Swin Transformer:

Swin Transformer suggests that a hierarchical framework with a shifted window can be used to compute self-attention efficiently. The reason why it is a non-overlapping window based system is that the image is partitioned into such windows and at this window, it is the self-attention that is determined. The movement of the windows between the stages is done to capture long range dependencies so that Swin Transformer can be more useful in working with high image resolution as compared to traditional transformers.

a) Mathematical Equations: The self-attention mechanism in the Swin Transformer is computed using:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (3)$$

Q (query), K (key) and V (value) are matrices based on what he/she puts in.

d k is the dimension of the key vectors.

The focus is drawn to local windows and the windows are moved to obtain world dependencies:

$$\text{Shifted Attention}(Q, K, V) = \text{softmax}\left(\frac{(Q+S)K^T}{\sqrt{d_k}}\right)V$$
(4)

where S represents the shift between windows.

The output of the Swin Transformer is then processed through hierarchical stages, progressively merging windows:

$$H_{l+1} = \text{Patch Merge}(H_l) \quad (5)$$

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where H_l is the output at layer l, and Patch Merge consolidates patches at higher resolutions.

3) VGG19:

VGG19 represents a convolutional neural network which contains 19 operational layers that include both convolutional and max-pooling and fully connected components. The system employs 3x3 convolution filters which serve as its basic operating filters, while maintaining its ability to extract features through a straightforward design. The depth of VGG19 enables the system to identify both minute details and broad visual elements, which makes it effective for image classification tasks.

a) Mathematical Equations: The convolution operation for a given layer in VGG19 is:

$$y_i = \text{ReLU}\left(\sum_j W_{ij} * x_j + b_i\right) \quad (6)$$

The weight matrix is referred to as W_{ij} where x_j is the input to the layer. The use of the convolution as an operation is denoted with the help of a $*$. whereas b should be denoted as b_i. The activation functional used to bring non-linearity is ReLU. In the case of max-pooling, it is done as a given function.

$$y_{i,j} = \max_{k,l}(x_{k,l}) \quad (7)$$

where $x_{k,l}$ represents the region in the input feature map, and the maximum value is selected for the output.

The output of the final fully connected layer in VGG19 is computed as:

$$y = \text{softmax}(W \cdot x + b) \quad (8)$$

W and b are the final fully connected layer weights and biases, and the output is normalized by use of softmax to give a classification.

V.RESULTS AND DISCUSSION

This part includes the analysis of the different deep learning systems on the data of the wheat plant disease and the comparison of the findings according to the accuracy, precision, recall, and F1-score. The researchers employed the models in conducting a comparison of the models and the comparison showed that they were capable of conducting proper classification of the diseases that affected wheat. The findings indicate that the state-of-the-art architectures, which employ the use of transformers, perform better than the conventional CNNs in case they are experiencing complex datasets. The results show that deep learning can be applied to the detection of diseases to automate it and allow timely process of the crops to reduce the extent of the damage done and better management of yields. The paper proposes certain enhancement of the upcoming models and their applications in agriculture that will be enacted on the real-life scenarios.

The confusion matrix of both models is in Fig.2, Fig.3 and Fig.4, which gives an in-depth analysis of the model results by giving the true positive, false positive, true negative, and false negative rates of identifying the disease of wheat plants.

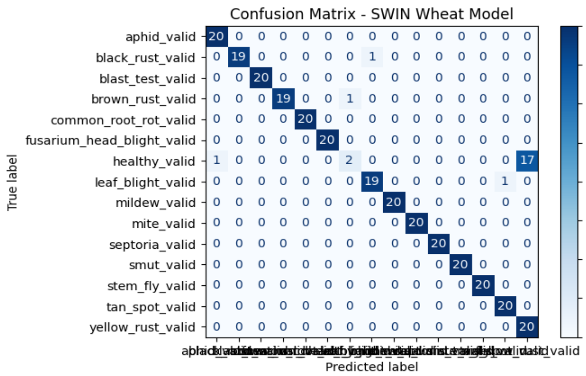

Fig. 2. Confusion metrics of swin transformer

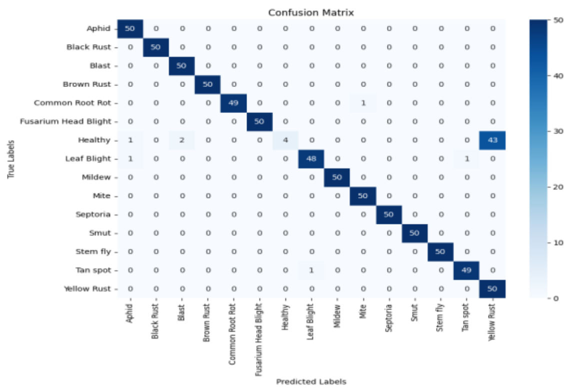

Fig. 3. Confusion metrics of densenet model

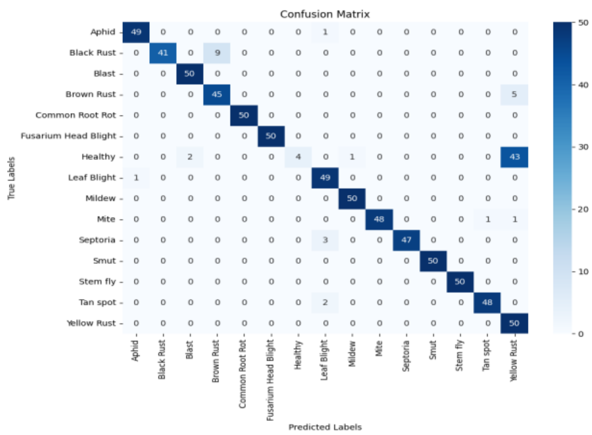

Fig. 4. Confusion metrics of vgg19 model

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The confusion matrices from Swin Transformer, DenseNet201, and VGG19 models show how well each model performs when it comes to diagnosing wheat plant diseases. The Swin Transformer system demonstrates high accuracy across all disease categories. It achieves nearly perfect results when classifying diseases, which include Aphid, Yellow Rust, and Fusarium Head Blight diseases. The system misclassifies cases of Mildew and Healthy patients, which shows that these two categories have some overlap in their identification process. The DenseNet201 model achieves accurate results because it successfully predicts most diseases, which include Aphid, Black Rust, and Yellow Rust. The system misclassifies some cases of the "Healthy" and "Mildew" diseases, but the system maintains high accuracy with only a few false positive and false negative results. The VGG19 system achieves satisfactory performance because it successfully identifies most diseases, which shows that it operates effectively. The categories.

A comparison on deep learning models to classify wheat disease is noted in Table 1. DenseNet has the highest accuracy (93 percent), high precision (0.96) and recall (0.93), which makes it the most reliable. Swin Transformer also has a result of 93% accuracy and significant accuracy higher than DenseNet. The accuracy of CNN is 90 percent, whereas ViT has an equal accuracy with slightly lower recall. NASNet is less precise and recall as expressed as having 88 percent accuracy. ResNet has the lowest accuracy of 75ol, which is certainly because of inadequate feature learning.

TABLE I. PERFORMANCE EVALUATION OF DEEP LEARNING MODELS FOR WHEAT DISEASE DETECTION

Model	Accuracy	Precision	Recall	F1 Score
CNN	0.90	0.90	0.88	0.89
DenseNet	0.93	0.96	0.93	0.92
NASNet	0.88	0.87	0.88	0.87
ResNet	0.75	0.77	0.75	0.74
Swin	0.93	0.94	0.93	0.92
VGG-19	0.91	0.94	0.91	0.89
ViT	0.90	0.90	0.90	0.89

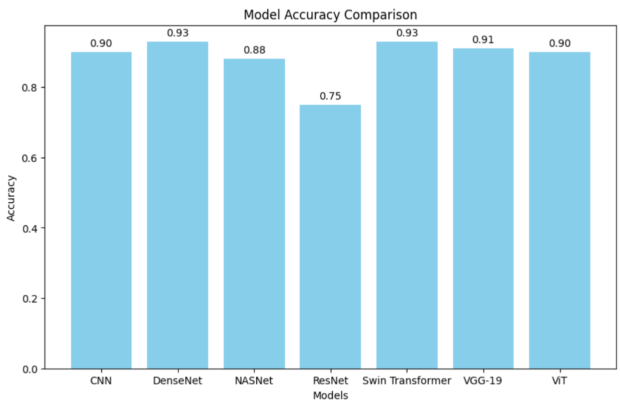

Fig. 5. Model Accuracy Comparision

The study discovered that a number of deep learning architectures such as CNN, DenseNet, NASNet, ResNet, Swin Transformer, VGG-19 and ViT were experimented on accuracy, precision, recall, and F1-score to predict wheat plant diseases. With an accuracy of 93, DenseNet and Swin Transformer were the highest-performing followed by VGG-19 with 91. ResNet had the lowest accuracy of 75 percent whereas NasNet and ViT had 88 percent accuracy and 90 percent accuracy respectively. The results preserve the high performance of the transformer-based models such as Swin Transformer compared to the traditional CNN models in the disease classification. This illustrates the capabilities of deep learning in accuracy agriculture in terms of the speedy and more accurate detection of diseases. Further research will cover optimization methods so that the performance can be enhanced.

VI. CONCLUSION

The study indicates that deep learning models including CNN, DenseNet, NASNet, ResNet, Swin Transformer, VGG-19, and ViT are quite useful in the detection of diseases related to wheat plants. The architecture in form of transformers was better than the conventional CNNs, especially when using complex data and identifying subtle variations in disease in order to obtain better accuracy, precision, recall and F1-score. The paper indicates the potential of deep learning in precision agriculture, early disease detection, minimizing crop

ISSN: 2583-6129
DOI: 10.55041/ISJEM.ACME002

losses, and enhanced yield forecasting. Further development will include the integration of hybrid models, hyperparameter optimization, and transfer learning resulting in a more accurate and enabling farmers to make a well-informed and timely decision to shift towards a more sustainable way of farming.

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