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WHEAT DISEASE DETECTION AND CLASSIFICATION USING RESNET152

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Abstract: Detecting and classifying crop diseases is crucial for maintaining crop productivity and quality. Traditional methods of crop disease identification are time-consuming and labour-intensive. Therefore, computer-based techniques have been developed to identify the disease automatically. Furthermore, wheat is the third most harvesting and consumed grain after rice and maize. Nowadays, crop disease detection is one of the leading research topics. Deep learning algorithms have recently been used to recognize and categorize various wheat diseases. This article describes a proposed deep learning-based method for detecting and classifying wheat diseases using a Residual Network (ResNet152), considered one kind of Convolutional Neural Network (CNNs). The proposed method achieves higher accuracy in identifying and classifying different types of wheat diseases than other existing methods. Moreover, it is observed through the results that the proposed approach provides the early detection and treatment of wheat diseases, leading to improved crop yielding and quality.

Keywords: **Convolution Neural Network, Deep learning model, Wheat crop disease, Image analysis, Performance evaluation**

I. INTRODUCTION AND RELATED WORK

Wheat is an essential crop providing food for billions of people worldwide. However, various diseases threaten its production and yield, which can significantly reduce the wheat crop's productivity. The Food and Agriculture Organisation says many people are undernourished due to a lack of food [1]. Early detection and timely management of these diseases are crucial to prevent crop losses and ensure food security. In this regard, image processing, artificial intelligence, machine learning, and deep learning algorithms have the ability to revolutionize the way for managing crop diseases in the agricultural field [2]. Using these techniques to give precise and timely details regarding the kind and severity of diseases affecting wheat crops can help farmers make informed decisions about disease management and prevent crop losses. Additionally, these techniques can monitor crop health over large areas, allowing for more efficient and effective disease management strategies. Furthermore, this discrepancy can be attributed to the farmer's access to more sophisticated equipment, information, and techniques. Various machine learning methods, including Decision Tree Techniques, Support Vector Machine Learning, Random Forest Models, K-Means clustering, Artificial Neural Networks, Convolutional Neural Networks, etc., have been used to identify and categorize various crop diseases. Alternative algorithms have been outperformed by techniques like decision trees and support vector machines. In this regard, Pranjali et al. [3] discuss plant leaf disease detection with the help of a support vector machine algorithm. A deep learning method-based multifunctional mobile application for plant disease detection was proposed by Uzhinskiy et al. [4]. An innovative framework for identifying a wheat-related illness that uses several more profound instances of learning and deals with crop images without any professional preprocessing was created by Lu et al. [5]. Zhu et al. [6] proposed machine learning-based dissimilarity between observed and simulated wheat yield shock data call for improvement in crop models. Jahan et al. [7] used machine-learning techniques to detect and classify wheat diseases. Further, Azadbakht et al. [8] also used the ML technique to recognize the rust in wheat leaves was investigated at the canopy size and LAI level. A practical ML-based framework for the automatic recognition and classification of various types of wheat diseases was discussed by Khan and Habib et al. [9]. The seriousness of wheat white powdery, as reported by [10] Khan and Imran Haider et al., was characterized using a machine learning-based chromatic analysis of images with a hyperspectral technique. The diagnosis of fusarium head blight in semolina wheat was investigated by Azimi et al. [11] used arithmetic and machine learning methods. Accurately detecting wheat diseases and prescribing the appropriate remedial actions can help farmers maximize their profits by minimizing crop losses, improving crop yields, and reducing costs. Recently, deep learning has been a powerful tool for detecting and classifying diseases in wheat crops. Convolutional Neural Networks (CNNs), such as deep learning techniques, have greatly improved image-based disease detection and classification accuracy and reliability. These algorithms can analyze large amounts of data and help recognize patterns indicative of different diseases affecting wheat crops. CNNs are widely used for image analysis, making them well-suited for automatically identifying and classifying wheat diseases. CNN is a deep learning algorithm commonly used for image recognition and computer vision tasks. Haider et al. [12] discussed a general approach for quickly recognizing and categorizing diseases affecting wheat crops using decision trees and CNN techniques. Zhang et al. [13] developed a CNN to accurately diagnose yellow wheat rust in the winter season using UAV images. Hasan et al. [14] have developed the detection of wheat spikes using CNN and done the corresponding analysis. Xu and Laixiang et al. [15] discussed a new deep learning technique (Google Net and Visual Geometry Group) that allows us to recognize wheat leaf diseases precisely. Goyal et al. [16] developed CNN based deep-learning model using VGG19 for wheat disease detection and classification. However, accuracy is not better, and also computational time is more.

Hence, in this article, an attempt has been made to develop wheat disease detection and classification using ResNet152. ResNet152 is a deep convolutional neural network. It is a part of the ResNet (short for Residual Network) family. ResNet152 has 152 layers and uses residual connections to help mitigate the vanishing gradient problem.

The rest of the article is followed as: Section 2 explains the existing wheat disease detection and classification work. Section 3 presents the methodology of the proposed system, including image processing, feature extraction, and classification techniques. Section 4 describes the results of the discussion of the proposed approach using an available dataset of wheat disease images. Finally, the article concludes in Section 5, which also covers future directions for research.

II. EXISTING WORK

The flow chart of existing work is given below in Figure 1.

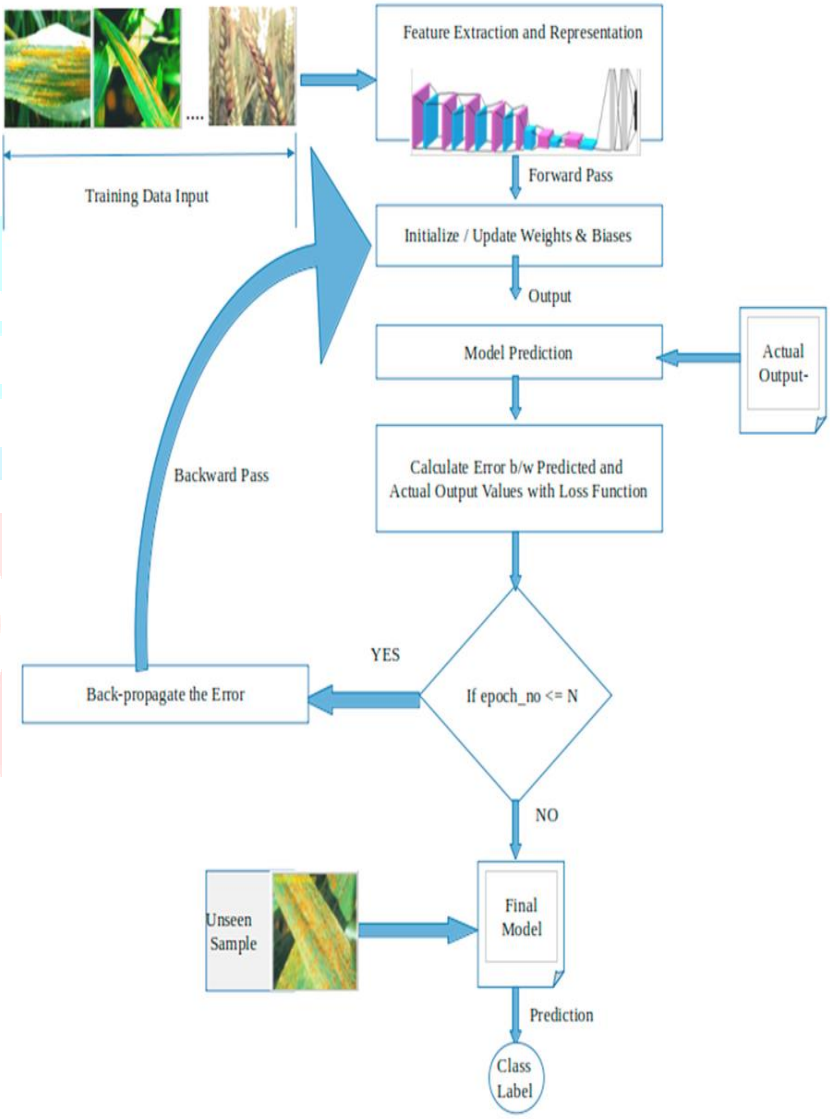

Fig. 1. Flow Diagram of Existing work [16]

Step 1: Data Collection
The first step is to collect images of wheat plants that are healthy, as well as pictures of plants that are affected by different types of diseases. These images should be of high quality and should represent a variety of different kinds of conditions and severities.

Step 2: Feature Extraction
The converting unprocessed raw data into actionable numerical features while keeping the information of the entire dataset. The amount of redundant data in the data set is reduced. In the end, reducing data makes it easier for the computer to build the model and accelerates the learning and generalization processes.

Step 3: Initialize weights and bias values
During the training process, the model is first presented with a set of input data and their corresponding desired output values. The model then uses its current weights and bias to predict each input, and the disparity between the expected output and the desired outcome is computed as the error or loss.

Step 4: Model
The VGG19 architecture is a convolutional neural network with 19 layers, including 16 layers of convolution and three layers of fully connected. The model structure comprises several convolutional blocks, each containing several convolutional layers ending with a max pooling layer. It is a variation of the VGG16 model and has 19 layers (hence the name) as opposed to 16 layers. It is illustrated in Figure 2.

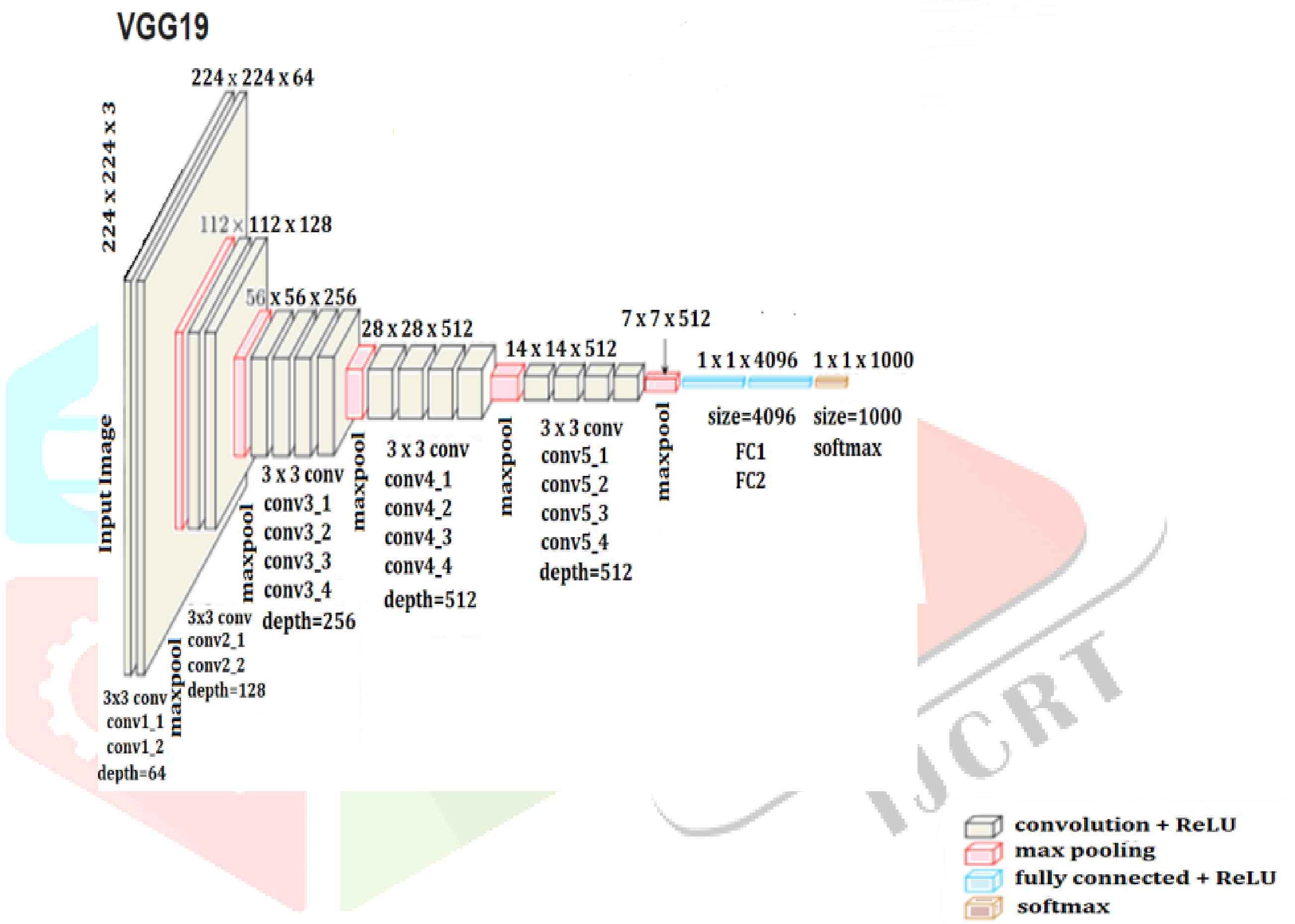

Fig. 2. VGG19 Architecture

III. PROPOSED WORK

The flow chart of proposed work is given below in Figure 3.

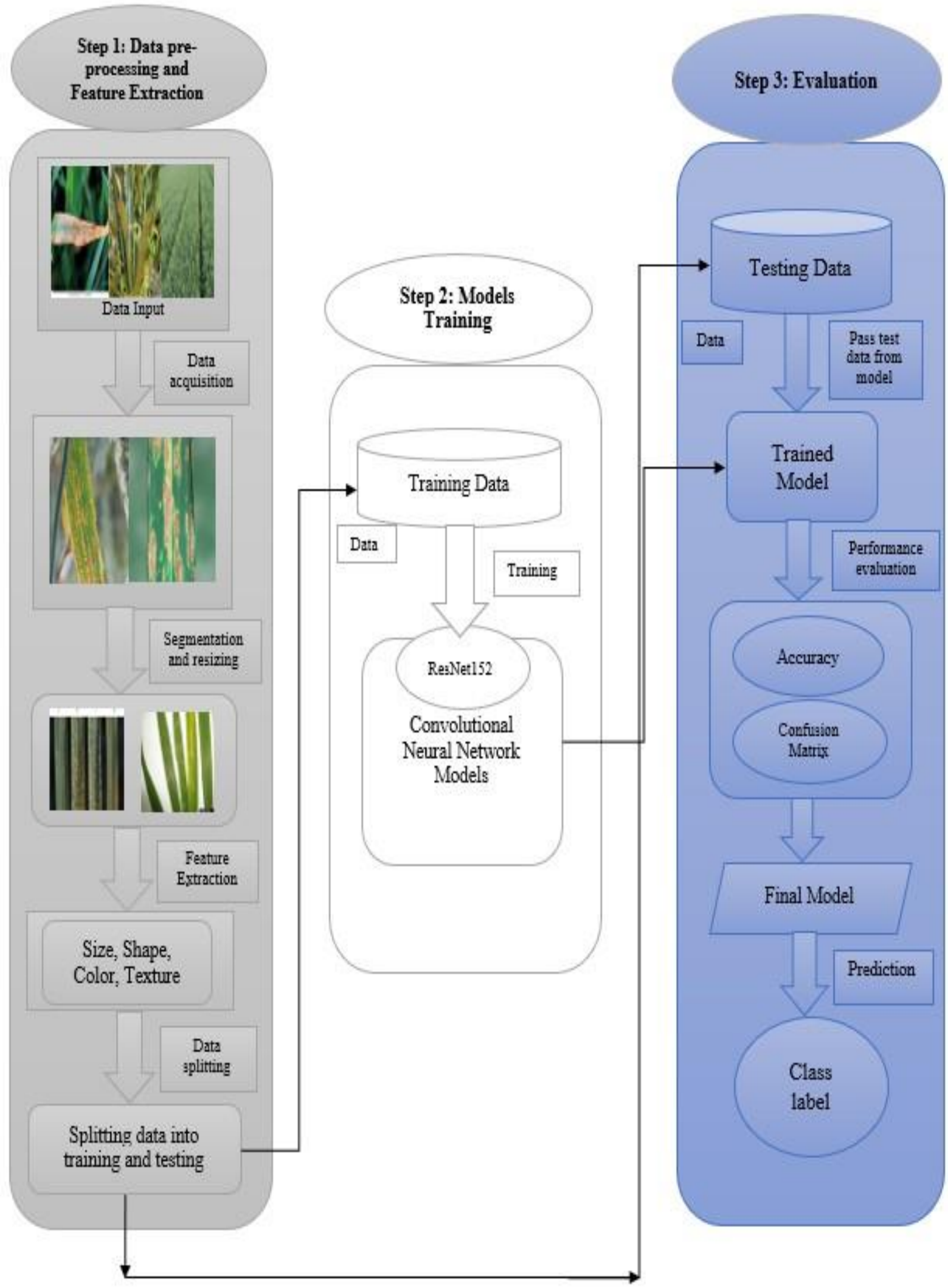

Fig. 3. Flow Diagram of Proposed method

Step 1: Data input refers to collecting and recording information related to various aspects of wheat diseases, such as the symptoms exhibited by infected plants, environmental conditions, and geographic location. This involves collecting a dataset of wheat images, which include both healthy and diseased plants.

Step 2: Data preprocessing: It is the cleaning, transforming, and preparing of raw data collected from various sources before it is used for analysis or modeling. The purpose of data preprocessing is to make it accurate, consistent, and analysis-ready.

Step 3: Data cleaning: The collected dataset may contain irrelevant or noisy data. Therefore, data cleaning is done to remove any unwanted data or images that are not related to wheat disease.

Step 4: Data augmentation: By performing various transformations, including rotation, flipping, and zooming, on the original images, new data formats are created. This can expand the dataset's size and strengthen the model.

Step 5: Image resizing and normalization: The input images must be resized to a fixed size and normalized for consistent lighting conditions. This makes it possible to learn from ideas with constant lighting conditions while reducing the data the model must process.

Step 6: Data splitting: The dataset is divided into training, validation, and testing sets. The training set is used to develop the model, the confirmation set to fine-tune its hyperparameters, and the testing set is used to analyze the model's performance.

Step 7: Model: ResNet152 (Residual Network)
ResNet-152 is a deep convolutional neural network model to classify images and identify objects. The model has 152 layers and is much deeper than the original ResNet-50 model. It uses skip connections and residual blocks to enable the training of deeper networks without experiencing the vanishing gradient problem. The residual blocks give the model to learn residual mappings, i.e., the distinction between a layer's input and output, which can be easily optimized during training. Instead of passing the output of each layer directly to the next layer, the output of the current layers is added to the actual output of the previous layers, allowing gradients to propagate more quickly through the network. The architecture of ResNet152 consists of a convolutional layer followed by several blocks of convolutional layers, each containing residual connections. The network also includes global average pooling and a fully connected layer for classification.

Step 8: Evaluate Model: After the model has been trained and validated, it is tested on the test set to see how well it performs on data that has yet to be seen. This step is crucial in determining whether the model is generalized well for analyzing new data.

Step 9: Interpretation of results: The evaluation results are interpreted to decide the model performance. For example, if the model achieves high accuracy and F1 score on both the validation and test sets, it is considered a reliable predictor of wheat disease. If the performance is unsatisfactory, adjustments may need to be made to the model or the dataset.

IV. RESULTS AND DISCUSSION

A. Experimental Settings

The suggested system is implemented in Google Collaboratory. A desktop with an 11th Gen Intel(R) Core (TM) i5-1135G7 @ 2.40GHz clock speed and 8 GB RAM is used for the experiments. Additionally, this uses a variety of libraries, including Python, a well-liked programming language. The most commonly used and supported version of Python is 3.7. Open-CV is a free machine learning software. It gives a variety of algorithms for computer vision tasks like object detection and the Python Matplotlib plotting library is used for data visualization. It is commonly used for creating graphs, charts, and other visualizations to analyze experimental results. Furthermore, the OS glob library is handy for file and directory manipulation. The training of the neural network with 200 epochs took 4 hours to complete.

B. Dataset

The Largest Wheat Disease Classification Dataset (LWDCD2020) with Fusarium head blight, healthy wheat, leaf rust, and the tan spot is a publicly available dataset designed to evaluate deep learning models for classifying wheat plant diseases. The dataset consists of images of wheat leaves captured from the field under natural lighting conditions. It is illustrated in Figure 4.

Fusarium Head Blight

Leaf Rust

Healthy Wheat

Tan Spot

Fig. 4. Sample Images chosen from the selected data set

C. Confusion Matrix

A confusion matrix is a table summarising how well a classification model performed regarding correct and incorrect predictions. It is a helpful tool for assessing the accuracy of the model's predictions. A table to compare the predicted and actual values. These components can compute several metrics, such as accuracy, precision, recall, and F1 score, providing valuable insights into the model's performance. The confusion matrix is frequently employed in binary classification issues but can also be expanded to multi-class problems. The confusion matrix table is given below in Figure 5.

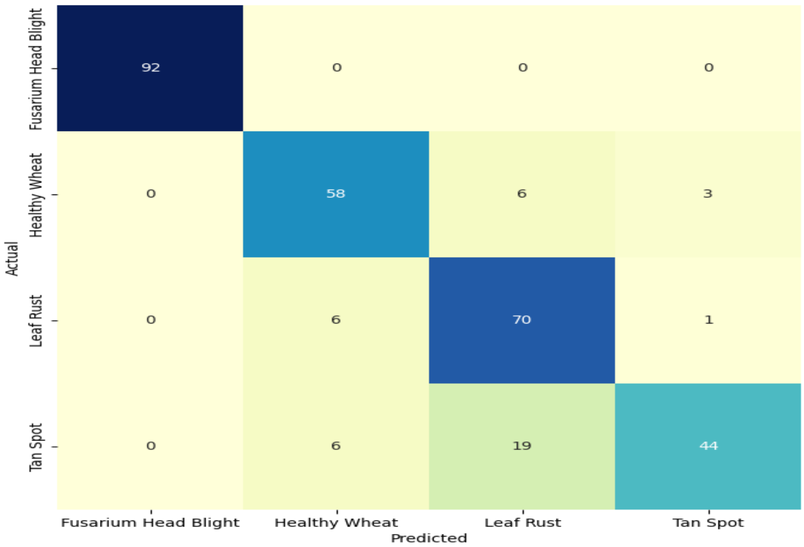

Fig. 5. Confusion Matrix

D. Evaluation Metrics

When a deep learning model is trained using a distinct training dataset, evaluation metrics are used to evaluate its performance on data that has yet to be seen. In a model considering the remaining 25% of unseen data, several metrics can be used to assess its performance. Such as, Accuracy, Precision, Recall, and F1-score. Accuracy is the proportion of accurate predictions obtained by the model based on unobserved data. Precision is the percentage of samples in which the model correctly predicted a positive result, Recall counts the number of genuinely positive pieces, and the mean value of Recall and precision is the F1 score.

E. Prediction Results

The prediction results for Fusarium Head Blight, Healthy Wheat, Leaf Rust, and Tan Spot are presented in Figure 6. respectively. Two images are provided as evidence for each prediction, demonstrating how accurately the proposed system performed the correct labels.
Table 1 shows the performance metrics evaluated for the proposed method and Table 2 compares existing and proposed methods.

Fusarium Head Blight

Healthy Wheat

Leaf Rust

Tan Spot

Fig. 6. The Prediction results for Fusarium Head Blight, Healthy Wheat, Leaf Rust, and Tan Spot.

TABLE 1 Performance Metrics of proposed method

TYPES OF WHEAT DISEASES	PRECISION	RECALL	F1-SCORE
Fusarium Head Blight	1.00	1.00	1.00
Healthy wheat	0.82	0.86	0.84
Leaf Rust	0.73	0.90	0.81
Tan Spot	0.91	0.63	0.77

The accuracy and loss of existing and proposed method is illustrated in Figure 7.

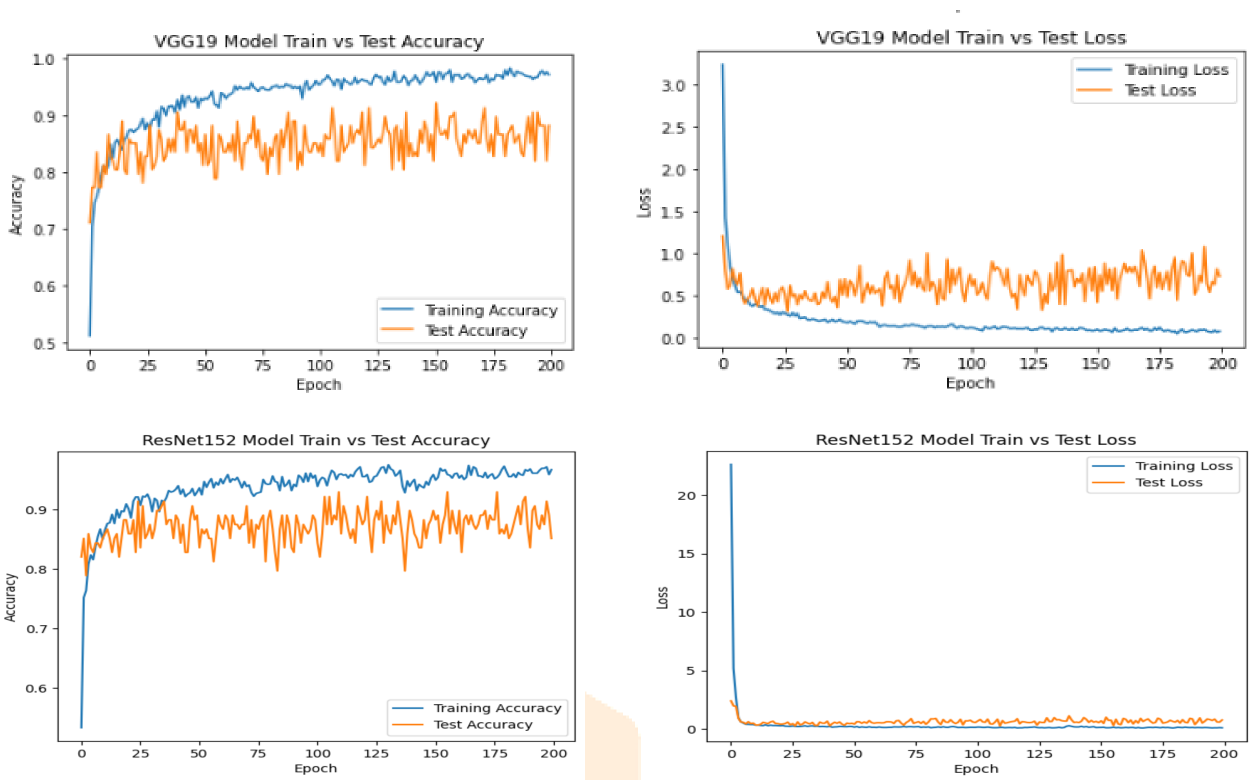

Fig. 7. Accuracy and loss of existing and proposed method

TABLE 2 Performance Comparison Between Existing and Proposed Method

MODEL	LAYERS	TRAINING ACCURACY	TESTING ACCURACY
Proposed Model (ResNet152)	152	97.81%	93.27%
Existing Model (VGG19)	25	94.14%	89.01%

V. CONCLUSION

With further improvements in data collection and the development of various disease detection, deep learning models have become an effective tool for precision agriculture, enabling farmers to make informed decisions and improve crop yields. Overall, applying deep learning models in agriculture help to increase food security, reduces waste, and improves sustainability in the long run. Hence, in this paper, a deep learning models for detecting and classifying wheat diseases is developed. The proposed method using the ResNet152 model shows promising results in detecting and classifying different types of wheat diseases, which can help farmers to take timely action to prevent crop damage and ensure a healthy harvest. It provides several advantages, such as high accuracy in identifying diseases affecting wheat crops and fast processing speed. The proposed model achieves a high testing accuracy of 93.27%, whereas the training accuracy is 97.81%. However, further research is needed to assess the model's performance on larger datasets and in different environmental conditions.

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