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Deep Learning Based Automated Wheat Disease Diagnosis System

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Abstract: It's critical to identify and categorize agricultural diseases. To preserve the quality and yield of crops. Crop disease identification using traditional methods takes a lot of time and labor. As a result, methods based on computers have been created to automatically diagnose the illness. In addition, behind rice and maize, wheat is the third most harvested and consumed grain. Crop disease detection is one of the most popular study subjects these days. Recently, several wheat illnesses have been recognized and categorized using deep learning algorithms. This article presents a Residual Network (ResNet152), regarded as one type of Convolutional Neural Network (CNN), and deep learning-based approach for identifying and categorizing wheat illnesses. Compared to other approaches now in use, the suggested method provides a greater level of accuracy in the identification and classification of various wheat illnesses. Furthermore, the results show that the suggested strategy offers early diagnosis and treatment of wheat illnesses, improving crop quality and output.
Keywords: Convolution Neural Network, Deep learning model, Wheat crop disease, Image analysis, Performance evaluation

I. INTRODUCTION

A vital crop that feeds billions of people globally is wheat. Unfortunately, a number of illnesses pose a threat to its yield and production, which can drastically lower the productivity of the wheat crop. Many people are undernourished as a result of a shortage of food, according to the Food and Agriculture Organization [1]. In order to prevent crop losses and guarantee food security, early detection and prompt management of these diseases are essential. Image processing, AI, machine learning, and deep learning algorithms, in this sense, have the potential to completely transform crop disease management in the agricultural sector. [2]. Farmers can manage illnesses and save crop losses by using these strategies to provide accurate and timely information about the kind and severity of diseases affecting wheat crops. Furthermore, by monitoring crop health over wide areas, these tools enable more effective and efficient tactics for managing diseases. Additionally, the farmer's access to more advanced tools, knowledge, and methods explains this difference.

II. LITERATURE REVIEW

One of the most significant crops and food sources in the world is wheat. Wheat leaf diseases, however, have a major effect on the plant's ability to grow. Sustaining the wheat industry and preserving wheat quality depend on accurate identification of wheat leaf diseases. Researchers suggest an integrated deep learning technique, known as RFE-CNN, that combines a convolutional neural network (CNN), elliptic metric learning (EML), feedback block (FB), residual channel attention block (RCAB), and elliptic metric learning (FB) to improve the accuracy of diagnosing wheat leaf illnesses. In order to extract fundamental characteristics from wheat leaves that were healthy and those that were sick, scientists first used two parallel CNNs. Then, to maximize these traits, residual channel attention blocks were used. The prior characteristics were then refined via feedback blocks, and a CNN and elliptic metric learning were used for processing and classification. According to experimental results, the suggested model performs better than VGG-19, ZFNet, GoogLeNet, Inception-V4, and Efficient-B7 in a number of areas, including decreased processing time, improved adaptability, and higher recognition accuracy. With a maximum testing accuracy of 99.95%, the overall classification accuracy attained was 98.83%. On open-source databases, the average accuracy score was 99.50%.

III. EXISTING RESEARCH

Step 1: Gathering Information Gathering photos of wheat plants in good health and those with various disease conditions is the first stage. These photos ought to be of the highest caliber and ought to depict a rangeof circumstances and intensities.

Step 2: Extraction of Features the process of retaining all of the dataset's information while transforming unprocessed raw data into useful numerical features. There is less redundant data in the data set. Ultimately, decreasing the amount of input speeds up the learning and generalization processes and makes it simpler for the computer to construct the model.

Step 3: Set up bias and weight values The model is initially given a set of input data and the associated desired output values throughout the training process. The difference between the expected output and the intended result is then computed as the error or loss, and the model uses its current weights and bias to predict each input. Step 4: Create a Model A convolutional neural network with 19 layers total—16 convolutional layers and 3 fully connected layers—is called the VGG19 architecture. A max pooling layer is the last layer in each of the several convolutional blocks that make up the model structure. It is a variant of the VGG16 model with 19 layers instead of 16, which is why it got its name.

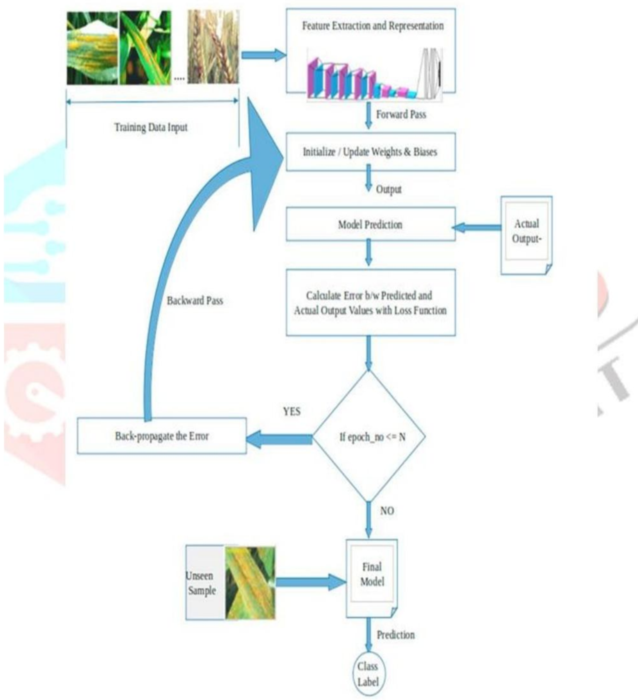
IV. PROPOSED WORK

1) Step 1: Gathering and documenting data on a range of wheat disease topics, including symptoms displayed by afflicted plants, environmental circumstances, and geographic location, is known as data input. This entails assembling a dataset of pictures of wheat plants, both in good health and in bad.
2) Step 2: Preparing the data: Before being used for analysis or modeling, raw data that has been gathered from multiple sources must be cleaned, transformed, and prepared. Preparing data for analysis is done to ensure accuracy, consistency, and readiness for analysis.
3) Step 3: Data cleaning: There's a chance that the gathered dataset has noisy or useless data. As a result, data cleaning is carried out to get rid of any unnecessary information or pictures unrelated to wheat disease.
4) Step 4: Data Augmentation: New data formats are produced by applying different transformations to the original photos, such as flipping, rotating, and zooming. This can increase the size of the dataset and improve the model.
5) Step 5: Image scaling and normalization: In order to ensure constant illumination, the input photographs need to be shrunk to a specific size and normalized. As a result, the amount of data the model has to process is decreased and it is able to learn from concepts with consistent lighting.
6) Step 6: Data splitting: Three sets of data are separated from the dataset: training, validation, and testing. The model is developed on the training set, its hyperparameters are adjusted on the confirmation set, and its performance is examined on the testing set.
7) Step 7: ResNet152 (Residual Network) as the model A deep convolutional neural network model called ResNet-152 is used to recognize objects and classify photos. The model is significantly deeper than the original ResNet-50 model, with 152 layers. To enable the training of deeper networks without running into the vanishing gradient problem, it makes use of residual blocks and skip connections. The model may readily learn residual mappings—that is, the difference between an input and output layer—through training thanks to the residual blocks. Gradients spread across the network more quickly because the output of the current layers is added to the real output of the preceding levels rather than being passed directly to the next layer.
8) Step 8: Evaluate Model: The model is tested on the test set to determine how well it works on data that hasn't been seen yet after it has been trained and verified. In order to assess how well the model is generalized for processing new data, this stage is essential.
9) Step 9: Interpretation of findings: The model's performance is determined by interpreting the evaluation findings. For instance, the model is regarded as a trustworthy predictor of wheat illness if it obtains high accuracy and F1 score on both the test and validation sets. The model or the dataset may need to be modified if the performance is not up to par.

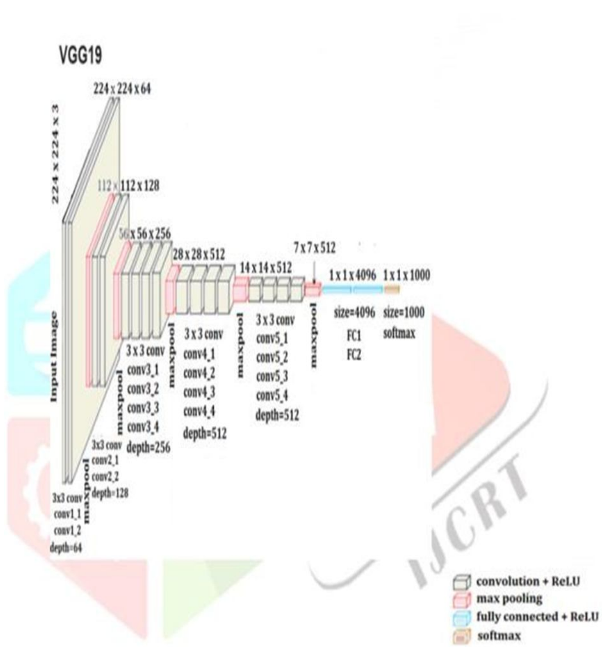
V. METHODOLOGY

There are numerous crucial elements in the process of creating an automated deep learning-based system for diagnosing wheat leaf disease. To ensure a varied portrayal of circumstances, first-rate datasets are gathered, including pictures of wheat leaves with various illnesses and healthy samples. After that, these photos undergo preprocessing to improve contrast, standardize size, and add data using methods like flipping and rotation to strengthen the model. The technique makes use of a convolutional neural network (CNN), which is able to automatically identify spatial hierarchies in picture data. With activation functions like ReLU to introduce non- linearity, the carefully crafted CNN architecture typically consists of layers like convolutional, pooling, and fully connected layers. Transfer learning can be applied to increase accuracy and shorten training times by employing pre-trained models (such as VGG and ResNet). Using methods like cross-validation, the model is trained on the labeled dataset in order to assess performance and prevent overfitting. To evaluate the efficacy of the system, performance indicators such as accuracy, precision, recall, and F1 score are calculated. Lastly, using fresh input photos, the trained model is used in an intuitive interface to enable real-time diagnosis of wheat leaf illnesses. The model is updated and monitored continuously to ensure that it remains accurate and flexible over time.

A. *Existing Model*



B. *System Architecture*



VI. RESULT

A publicly accessible dataset called the Largest Wheat Disease Classification Dataset (LWDCD2020) includes information on leaf rust, tan spot, Fusarium head blight, healthy wheat, and other wheat plant diseases. Its purpose is to assess deep learning algorithms for the classification of these illnesses. The photos in the collection are of wheat leaves taken in the field with ambient lighting.

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Fusarium Head Blight

Healthy Wheat

Tan Spot

Leaf Rust

A. *Prediction Results*

```
Image: crr_1.jpg Predicted Label: [0. 0. 0. 1.]
Image: crr_2.jpg Predicted Label: [0. 0. 1. 0.]
Image: h_1.jpg Predicted Label: [0. 0. 0. 1.]
Image: h_2.jpg Predicted Label: [0. 0. 0. 1.]
Image: lr_1.jpg Predicted Label: [1. 0. 0. 0.]
Image: lr_2.jpg Predicted Label: [0. 0. 1. 0.]
Image: ls_1.jpg Predicted Label: [0. 1. 0. 0.]
Image: ls_2.jpg Predicted Label: [0. 1. 0. 0.]
```

The predicted results are stored in an array which determines what type of wheat leaf the input image is. In this case: 0 0 0 1 for Fusariam Head Blight, 0 0 1 0 for Healthy Wheat, 0 0 0 1 for Tan Spot, 1 0 0 0 for Leaf Rust etc…

VII. CONCLUSION

Deep learning models have developed into an efficient tool for precision agriculture, helping farmers to increase crop yields and make well-informed decisions. This is due to ongoing advancements in data collecting and the creation of diverse disease detection techniques. In general, the use of deep learning models in agriculture increases food security, lowers waste, and enhances sustainability over time. Therefore, a deep learning model for identifying and categorizing wheat illnesses is created in this article. Promising results are shown in the detection and classification of several wheat illnesses by the suggested method utilizing the ResNet152 model. This can assist farmers in taking prompt action to prevent crop loss and guarantee a healthy harvest. Fast processing speed and great accuracy in identifying wheat crop diseases are just two of its many benefits.

While the training accuracy is 97.81%, the suggested model has a high testing accuracy of 93.27%. To evaluate the model's performance on bigger datasets and in various environmental settings, more investigation is necessary.

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