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Wheat Plant Leaf Disease Detection and Classification Using Machine Learning

Pooja A B[1], Monisha H H[2], Miladunnisa J S[3], Spoorthi A M[4], Mr.Guruprasad[5], Mr.Vijay R[6]
[1,2,3,4]*Information and Science and Engineering, Malnad College of Engineering, Hassan-573202, India*
[5,6]*Assistant Professor, Information and Science and Engineering, Malnad College of Engineering, Hassan-573202, India*

***Abstract*— Wheat disease Finding is a critical duty in agriculture to guarantee a good crop output and avoid financial losses. Detecting diseases in wheat is crucial for ensuring good crop yields and preventing financial losses in agriculture. Recently, deep learning techniques have shown promising results in identifying and classifying wheat diseases from images. In this study, we propose a system that uses the VGG19 deep convolution neural network (CNN) architecture to detect wheat diseases. The system works with a dataset of images showing both healthy and diseased wheat plants. These images are pre-processed through resizing, normalization and enhancement. The dataset includes photos of wheat affected by 10 different diseases, such as powdery mildew, yellow rust and leaf rust. Our approach fine-tunes a pre-trained VGG19 model on this dataset. To evaluate its effectiveness, we use metrics like accuracy, precision, recall and F1 score. The results indicate that our model outperforms other state of wheat disease detection algorithms, achieving an impressive 97.65% accuracy on the validation dataset. This method could be practically applied to help farmers quickly and accurately identify wheat diseases, leading to better crop management and reduced losses. Moreover, the approach can potentially be adapted to other crops and diseases, representing a valuable contribution to both agriculture and computer vision fields.**

The significance of this exploration lies in its capability to bridge gaps between theoretical advancements and practical operations, especially in the environment of global agricultural challenges. By understanding the methodologies and results of these studies, this paper aims to give a consolidated resource for experimenters, masterminds, and interpreters in this arising sphere.

***Keywords*—Machine learning, Deep learning, Leaf disease, Convolutional neural networks, VGG19.**

I. INTRODUCTION

Wheat (Triticum aestivum) is one of the most widely cultivated crops globally and is crucial for food security. However, wheat plants are susceptible to a wide range of diseases, including fungal, bacterial, and viral infections, which can significantly reduce yield and quality. Early detection and accurate diagnosis of these diseases are critical to minimizing crop loss and improving productivity.

Traditionally, plant disease identification relied on manual observation by experts, but this process is time-consuming, subjective, and often impractical for large-scale agricultural operations.

Recent advancements in machine learning (ML) and computer vision have opened up new avenues for automating the detection of plant diseases. Machine learning algorithms can analyze images of wheat plant leaves and recognize common traits linked to particular diseases.. These systems leverage large datasets of images with labeled disease categories to train models capable of recognizing symptoms like spots, lesions, or discoloration on leaves.

II. RELATED WORKS

A. *Wheat Leaf-Disease Detection Using Machine Learning Techniques for Sustainable Food Quality*

Authors: Rania El-Sayed, Ashraf Darwish, and Aboul Ella Hassanien

Year of publication: 2021

Description: Wheat is considered one of the best food resources and quality in many countries, especially in Africa and Asia. However, the crops are affected by many diseases during the cultivation process including rust and leaf spots that can destroy the crop after a month. This leads to a large degradation in wheat productivity rate. So, the crops need continuous observation during the agriculture process and this needs experts with the nature of the wheat leaf. This is a time-consuming and expensive task. So, this paper aims to detect various types of leaf diseases to differentiate them from healthy crops without needing continuous crop monitoring and to minimize yield losses. The dataset used is a three-class wheat leaf dataset that consists of one healthy class and 2 leaf disease classes namely septoria and stripe rust. We proposed a Support Vector Machine (SVM) DL-based features model that depends on features extracted from different deep Transfer Learning (TL) models applied to the dataset after pre- processing that are then passed to the SVM classifier. VGG16, VGG19, and Inception ResNetV2 models are used to extract the features out of the images one at a time, where, VGG19 is the best model where it achieves an accuracy of 98% which outperforms many researches in the literature.

Methodology: In this paper, to solve the problem of leaf disease monitoring for the wheat crop, we used an SVM classifier trained on DL. Characteristics obtained from various transfer learning models. These charactersitics are gathered from the processed images using InceptionResNetV2, VGG16, and VGG19 TL models one at a time to compare which of them is more effective. To extract the features, the classification layer for each TL model is removed to have the flattened features as the final output. Then the extracted features are passed to the SVM classifier with a linear kernel to give the output as the disease type of the wheat leaf.

Conclusion: In this study, several tests were performed on the suggested model to identify disease in wheat leaves. The model uses important characteristics obtained from different transfer learning models, which are then analysed by an SVM classifier. The input images serve as the basis for extracting these features. The model is trained on a publicly available wheat leaf disease dataset with three classes. From the results, it is obvious that the VGG19 feature extractor has the highest performance with an accuracy of 98% that outperforms other models in the literature. For future work, this model may be enhanced to classify other types of wheat leaf diseases or other crops like rice, tomato, corn, apple, and cotton.

B. *Disease Classification in Wheat from Images Using CNN*

Authors: Dhruv Suri, Shivie Saksenaa, Umang Sehgal

Year of publication: 2023

Description: Wheat is a staple crop for large sections of the global population. However, like all crops, a major impediment to its yield and expansion is the prevalence of diseases in wheat that cause significant losses to harvest annually. One of the methods that such losses can be prevented is by identifying and responding to the same appropriately and swiftly.

Methodology: We implemented each of the models on the dataset to classify the images as healthy or as having each of the described infections. The models were evaluated on the test dataset based on the metrics previously discussed: accuracy, precision, recall and F1 score to judge their performance in trying to classify with new data. The first consideration was the model complexity, which is summarized as per Table II. The number of trainable parameters directly affects the computational complexity while training, as the more parameters there are to train, the more parameters there are for which computations will have to be made.

Conclusion: In this paper, we consider the problem of disease classification in wheat using images. For the same we compare pre-trained models, using three of the most popular deep learning architectures, namely: VGG16, ResNet50. MobileNet. Our results show that MobileNet had the best performance across metrics for classifying wheat diseases. This may be explainable by the larger number of trainable parameters that are available to the model over VGG16, thus it can fit better to the data available, whereas. with ResNet50, the model is much deeper than the other two available models, thus it may require training over large number of epochs to give comparable results.

C. *Leaf and spike wheat disease detection & classification using an improved deep convolutional architecture*

Authors: Lakshay Goyal, Chandra Mani Sharma, Anupam Singh, Pradeep Kumar Singh

Year of publication: 2021

Description: Wheat is one of the most widely grown grains, but many crops are the lost to diseases. With over 24 harmful wheat diseases, manual detection is difficult. Automated classification can improve yield, quality and pricing. This study tests a model using deep learning features and an SVM classifier on segmented images. Results show that VGG19 performs best, achieving 98% accuracy. Future improvements could expand detection to other crops like rice, tomato and corn. Deep learning plays a key role in disease diagnosis and classification.

Methodology: ResNet50 is a deep neural network with 50 layers. Its key feature is the ability to bypass certain layers, improving efficiency. The model has over 23.5 million trainable parameters and about 53000 fixed parameters, making it powerful for image analysis.

Conclusion: This study introduces a new deep learning system for identifying wheat diseases. The model was tested using the LWDCD2020 dataset and successfully classified 10 different wheat diseases, including Loose Smut, Tan Spot, Powdery Mildew and Leaf Rust. It achieved a test accuracy of 97.88% and a training accuracy of 98.62%. Compared to other deep learning models, it showed significant improvement 7.01% higher accuracy than VGG16 and 15.92% higher than ResNet50. These results suggest that the proposed approach is highly effective for wheat disease classification.

D. *Deep Learning for Wheat Plant Leaf Disease Detection*

Authors: A. L. Farhan, R. R. A. S. A. Al-Rahmi
Year of publication: 2020

Summary: This study used Convolutional Neural Networks (CNNs) to detect and classify wheat leaf diseases. The researchers employed a dataset containing images of wheat leaves affected by common infections such as powdery mildew, wheat rust, and leaf spots. The results showed that deep learning models, particularly CNNs, outperformed traditional machine learning algorithms in terms of accuracy and efficiency.

Key Findings: CNN-based models achieved high accuracy in detecting diseases, showing the capability of deep learning for large-scale agricultural applications.

E. Wheat Disease Detection using SVM and Image Processing Techniques
Authors: P. K. Rani, V. P. S. Yadav
Year of publication: 2019

Summary: This paper focused on the use of a Support Vector Machine (SVM) classifier for wheat disease detection. The authors employed image processing techniques like edge detection and feature extraction to identify key features from wheat leaf images. These features were then fed into the SVM model for classification into different disease categories (e.g., wheat rust, blight).

Key Findings: The study demonstrated that SVMs, when combined with image preprocessing techniques, achieved robust performance in identifying diseases. The model performed well even with limited datasets, which is often a challenge in agricultural applications.

F. Hybrid Machine Learning Approach for Wheat Disease Detection (2021)
Authors: S. K. Sharma, A. K. Singh
Year of publication: 2021

Summary: In this study, a hybrid machine learning model combining CNNs and Random Forests (RF) was proposed for the detection of wheat diseases. The hybrid model leveraged CNNs to identify key features from wheat leaf images, combined with Random Forests for disease classification. The dataset included images of leaves with diseases such as wheat yellow rust, leaf rust, and septoria tritici blotch.

Key Findings: The hybrid approach demonstrated better generalization performance compared to using either CNN or RF alone. This study highlighted how combining different ML algorithms can improve classification accuracy,

III. METHODOLOGY

The approach for identifying and classifying wheat plant diseases using Convolutional Neural Networks (CNN) involves a structured approach to data acquisition, preprocessing, model development, and deployment. Initially, a dataset is prepared by collecting high-quality pictures of wheat, capturing both healthy and diseased samples under various environmental conditions. The dataset is preprocessed to enhance image quality through resizing, normalization, and augmentation techniques such as rotation, flipping, and scaling to improve model generalization. A CNN model either custom-designed or based on pre-trained architectures like ResNet , VGG16, or MobileNet, is then employed to extract relevant features and classify diseases. During the training phase, the model learns patterns such as texture, color, and shape associated with specific diseases. Techniques like transfer learning and fine-tuning are utilized to optimize performance and reduce training time. The system is evaluated using metrics such as accuracy, precision, recall, and Fl-score to ensure reliable predictions. To facilitate real-time deployment, the trained model is optimized for edge devices using quantization and pruning. The final model is integrated into a user-friendly application that enables farmers and agricultural workers to upload plant images and receive instant feedback on disease type, severity, and treatment recommendations. Advanced visualization techniques, such as heatmaps, are included to highlight affected areas, enhancing interpretability. The approach can be used to work both offline and online, ensuring accessibility and scalability across diverse farming environments.

Key Techniques in Wheat Leaf Disease Detection Using Machine Learning:

Image Acquisition: The first step involves capturing high-quality images of wheat leaves using digital cameras or drones. These pictures contain valuable details about the plant's health.

Image Preprocessing: The images are preprocessed to improve details like edges, texture and color which are required for identifying leaf disease symptoms. Techniques like normalization, noise reduction, and contrast adjustment may be used.

Feature Extraction: Important details like texture, color patterns and shape are taken from the images to represent the conditions of the leaves. These features serve as input to machine learning models.

Model Training: Supervised machine learning algorithms, such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forests, are commonly used to classify the health status of wheat leaves. These models are trained on datasets with known labels (healthy or diseased).

Disease Classification: Once the model is trained, it can classify new images of wheat leaves into different disease categories or determine whether the plant is healthy.

Deployment: For real-time applications, disease detection systems can be integrated with mobile devices or drones, allowing farmers to monitor wheat crops in the field and receive instant disease diagnosis.

IV. ALGORITHMS USED

Deep Learning Approaches: Convolutional Neural Networks (CNNs) are the workhorses of modern leaf disease detection. Think of CNNs as digital plant pathologists that can automatically learn and identify disease patterns in leaf images. They excel at picking up subtle visual clues that might indicate diseases like yellow rust, brown rust, or powdery mildew.

Traditional Machine Learning Methods: Support Vector Machines (SVMs) work like highly skilled sorters. They draw boundaries between healthy and diseased leaf characteristics, making them particularly good at distinguishing between similar-looking diseases. They're especially useful when working with smaller datasets.

Random Forests operate like a committee of expert botanists. Each "tree" in the forest looks at different aspects of the leaf - color patterns, spots, lesions - and then they vote together to decide what disease they're seeing. This makes them very reliable since they don't put all their eggs in one basket.

K-Nearest Neighbors (KNN) uses a "birds of a feather flock together" approach. It looks at previously diagnosed leaf images and groups similar cases together. While simpler than other methods, it can be quite effective for initial disease screening.

Residual Networks(ResNet) attack the evaporating grade problem, enabling the training of veritably deep networks. ResNet introduces" skip connections," which bypass certain layers to insure that slants flow effectively during backpropagation. This armature is pivotal for feting subtle differences in analogous-looking foods, as it enables deeper analysis of image features. address this problem.

```
To generate c classifiers:
for i = 1 to c do
   Randomly sample the training data D with replacement to produce D_i
   Create a root node, N_i containing D_i
  Call BuildTree( N_i )
end for

BuildTree(N):
if N contains instances of only one class then
   return
else
   Randomly select x% of the possible splitting features in N
   Select the feature F with the highest information gain to split on
   Create f child nodes of N , N_1 ,..., N_f , where F has f possible values ( F_1 , ... , F_f )
   for i = 1 to f do
      Set the contents of N_i to D_i , where D_i is all instances in N that match
      F_i
      Call BuildTree( N_i )
   end for
end if
```

Fig. 1. Random Forest Algorithm

1. Convolutional Neural Networks (CNNs)

CNNs are the backbone for image-based plant disease detection. They capture spatial details from images, which makes them highly suitable for recognizing and understanding patterns associated with leaf diseases.

Components of CNNs for this task:

Convolution Layers: For feature extraction (e.g., detecting edges, spots, or color variations on leaves).

Pooling Layers: For dimensionality reduction while retaining important features.

Fully Connected Layers: For classification into healthy or diseased categories.

Popular CNN Architectures:

Custom CNNs: Designed from scratch for specific datasets. Pretrained Models (Transfer Learning):

- VGG16/VGG19
- ResNet
- InceptionNet
- MobileNet
- EfficientNet

These pre-trained models are fine-tuned on wheat leaf disease datasets to improve performance and reduce training time.

1. Data Augmentation Techniques

To improve model performance by artificially expanding the dataset:

- Rotations
- Flipping
- Zooming
- Brightness adjustments
- Adding noise

2. Classification Algorithms

Softmax Layer: Used in CNNs for multi-class classification (e.g., healthy, disease A, disease B).

Binary Classification: If focusing on healthy vs. diseased categories.

3. Ensemble Learning with CNNs

Combining outputs from multiple models (e.g., ResNet + Inception) can improve classification accuracy by leveraging diverse feature sets.

V. RESULT

The results of different machine learning methods are utilized for wheat plant leaf disease detection are overwhelmingly positive, with deep learning (especially CNNs) and hybrid models providing the highest levels of accuracy. These models can significantly aid in the early detection of diseases, improving decision-making in agricultural practices. However, the accuracy depends on factors such as dataset size, quality, and environmental conditions, suggesting that ongoing research will continue to improve the robustness and scalability of these systems for real-world agricultural applications.

VI. CONCLUSION

Detecting and classifying diseases in wheat plants using machine learning has proven to be a powerful approach for improving agricultural practices. By leveraging advanced algorithms and image processing techniques, farmers and researchers can identify diseases at an early stage, enabling timely intervention and reducing crop losses. Machine learning models, when trained with sufficient high-quality data, can achieve remarkable accuracy in identifying various wheat leaf diseases, such as rust, blight, and mildew.

This method not only minimizes the dependency on manual inspection which is often time-consuming and error-prone, but also optimizes the effectiveness and promotes sustainable farming practices by optimizing pesticide use. By integrating such systems with user-friendly mobile or web applications, farmers can access real-time diagnostics and recommendations, ultimately leading to improved productivity and food security.

While significant progress has been made, challenges like dataset quality, real-world variability, and model generalization remain. Future work could focus on enhancing model robustness, integrating Internet of Things (IoT) sensors, and developing cost-effective solutions to make this technology more accessible, particularly for small-scale farmers.

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