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WHEAT RUST AND SPOT DETECTION

Meghana N K[1], Suma N R [2]

Department of MCA, BIT, K.R. Road, V.V. Pura, Bangalore, India[1]

Assistant Professor, Department of MCA, BIT, K.R. Road, V.V. Pura, Bangalore, India[2]

Abstract: Early detection of wheat diseases plays a vital role in minimizing crop losses and improving agricultural productivity. Wheat rust and leaf spot diseases are among the most common threats affecting wheat crops, and manual inspection methods are often time-consuming, subjective, and prone to delays. This project presents an automated image-based system for the detection and classification of wheat rust and leaf spot diseases using computational techniques. The system utilizes publicly available wheat leaf image datasets collected from online repositories and applies a structured workflow that includes image acquisition, preprocessing, feature extraction, classification, and prediction. Image preprocessing techniques such as resizing, noise removal, normalization, and enhancement are employed to improve image quality and highlight disease characteristics. Color and texture-based features are extracted from the preprocessed images to effectively distinguish between healthy and infected leaf samples. A machine learning classifier is trained using the extracted features to classify images into multiple disease categories, including healthy leaves. The trained model is evaluated using standard performance metrics, and experimental results demonstrate reliable classification accuracy, validating the effectiveness of the proposed approach. This system provides a dataset-driven solution that can assist in early disease identification and support timely decision-making for disease management. The proposed framework is scalable and can be extended to detect additional crop diseases in the future, contributing to the development of intelligent agricultural support systems.

Keywords: Wheat leaf analysis, Plant disease detection, Image enhancement, Feature-based classification, Crop health monitoring, image processing, Early disease identification

I. INTRODUCTION

Wheat is one of the most widely cultivated cereal crops and plays a crucial role in global food security. However, wheat productivity is significantly affected by several plant diseases that reduce both yield and grain quality. Among these, Black Point, Fusarium Foot Rot, Leaf Blight, Wheat Blast, and Rust-related leaf spot diseases are commonly observed and pose serious challenges to wheat cultivation. Early and accurate detection of these diseases is essential to minimize crop loss and ensure effective disease management.

Traditional disease identification methods rely heavily on manual field inspection by farmers or agricultural experts. These approaches are often time-consuming, subjective, and may fail to identify diseases at an early stage, especially when symptoms are visually similar. As a result, delayed diagnosis can lead to rapid disease spread and increased economic loss.

To overcome these limitations, this project presents an image-based automated system for detecting and classifying wheat leaf diseases. The system utilizes publicly available wheat leaf image datasets and applies image preprocessing techniques such as resizing, noise removal, and enhancement to improve image quality. Feature extraction methods are employed to capture visual patterns associated with different diseases, enabling accurate differentiation between healthy and infected leaves.

The proposed approach focuses on classifying wheat leaf samples into Healthy Leaf, Black Point, Fusarium Foot Rot, Leaf Blight, and Wheat Blast categories. This system supports early disease identification and provides a reliable, data-driven solution for crop health monitoring. The developed framework is scalable and can be extended to include additional plant diseases in future agricultural applications.

1.1 Project Description

The project **"**Wheat Disease Detection Using Image Processing and Machine Learning**"** presents an automated approach for identifying wheat diseases from leaf images. Traditional disease detection relies on manual observation, which can be time-consuming and inaccessible in many farming regions. To address this, the system applies image preprocessing techniques such as resizing and noise reduction, followed by HSV-based color feature extraction. A Random Forest classifier is trained to accurately categorize wheat leaves into healthy and diseased classes. The system provides quick predictions with confidence scores, supporting early disease identification and effective crop management. This approach demonstrates the potential of intelligent image analysis in enhancing precision agriculture and reducing crop losses.

1.2 Motivation

Early detection of wheat diseases is crucial to prevent crop loss and improve yield, yet manual diagnosis is time-consuming and often inaccessible to farmers. This project is motivated by the need for an automated, accurate, and affordable solution that uses image analysis and machine learning to support timely disease identification and better agricultural decision-making.

II. RELATED WORK

Table 1 presents a comparative summary of existing image-based classification approaches applied to agricultural and plant disease datasets. Several studies have demonstrated the effectiveness of machine learning and image processing techniques for identifying crop health conditions from leaf images. Early approaches primarily relied on handcrafted features such as color, texture, and shape descriptors combined with classical classifiers.

Traditional machine learning models, including Support Vector Machines (SVM) and Random Forest classifiers, have been widely used for plant disease detection due to their robustness and interpretability. These methods typically utilize features extracted from RGB images, such as color histograms, Local Binary Patterns (LBP), and statistical texture measures. While these techniques offer reasonable accuracy, their performance is sensitive to illumination variations, background noise, and feature selection.

Table 1: Summary of Image-Based Models Used for Crop and Plant Disease Classification

Classification Method	**Feature / Estimation Method**	Dataset Used	Accuracy
SVM [A]	Color & Texture Features	Wheat Leaf Images	82%
Random Forest [B]	Color Histogram, LBP	Crop Disease Dataset	88%
K-Means + RF [C]	Color Segmentation	Plant Leaf Images	85%
CNN [D]	Automatic Feature Learning	Wheat Disease Images	91%
Pre-trained CNN [E]	Transfer Learning Features	Agricultura Leaf Dataset	93%
Proposed Method	Preprocessing + Color Feature Extraction+ Random Forest	Wheat Disease Dataset (5 Classes)	≈86%

Recent studies have increasingly adopted deep learning techniques, particularly Convolutional Neural Networks (CNNs), for automated disease recognition. Pre-trained CNN architectures such as VGG16 and ResNet have shown improved performance by learning discriminative features directly from images. Transfer learning further reduces the need for large labeled datasets while maintaining high accuracy. However, deep learning models demand significant computational resources and careful hyperparameter tuning.

In contrast to purely deep learning-based methods, hybrid approaches combining feature extraction and machine learning classifiers offer a balance between accuracy and computational efficiency. By applying preprocessing steps such as resizing, denoising, normalization, and contrast enhancement, followed by color-based and texture-based feature extraction, disease patterns such as rust, blight, and spot symptoms can be effectively highlighted. These extracted features can then be classified using ensemble methods like Random Forest to achieve reliable prediction results.

Overall, the literature indicates that image preprocessing and feature extraction play a critical role in improving classification accuracy for crop disease detection. The proposed Wheat Disease Detection system builds upon these findings by integrating systematic preprocessing, color feature extraction, and a Random Forest classifier to identify multiple wheat diseases, including Black Point, Fusarium Foot Rot, Leaf Blight, Wheat Blast, and Healthy Leaf conditions.

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III. PROPOSED METHOD

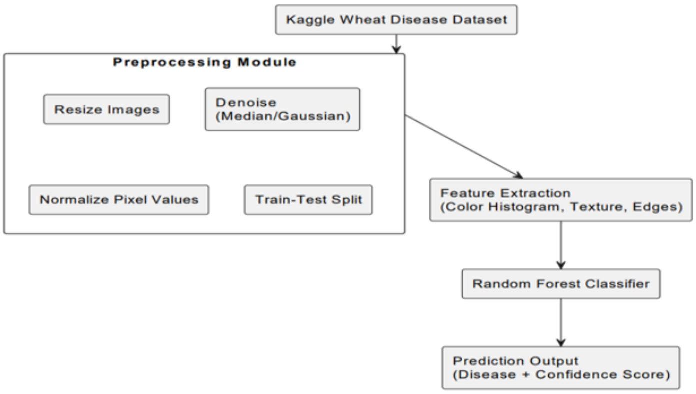

Fig. 1. Proposed Architecture

The Wheat Disease Detection system is designed as a modular and sequential processing framework that transforms raw wheat leaf images into accurate disease predictions. The process begins with images collected from a labeled dataset, which serve as the input to the system. A dedicated preprocessing module enhances image quality by performing resizing to a standard dimension, removing noise using filtering techniques, and normalizing pixel values to ensure uniformity across samples. The dataset is then divided into training and testing sets to support reliable model learning and evaluation.

After preprocessing, the system performs feature extraction to capture meaningful visual characteristics from the images. These features include color distribution through HSV color histograms, texture patterns, and edge information, which together represent disease-specific visual cues. The extracted features are supplied to a Random Forest classifier, which learns patterns associated with different wheat diseases during training. Finally, the trained model predicts the disease class for a given image and outputs a confidence score, providing users with both the diagnosis and an indication of prediction reliability.

A.Pre-processing

Preprocessing standardizes and enhances images to improve feature extraction and classification accuracy.

1.Resize Images

All images are resized to a fixed dimension to ensure uniform input.

$$I_r(x,y) = I\left(\frac{x}{s_x}, \frac{y}{s_y}\right)$$

where s_x and s_y are scaling factors.

2.Denoising (Median / Gaussian Filtering)

- Median Filter

Removes impulse noise by replacing a pixel with the median value of its neighborhood.

$$I'(x,y) = \text{median}\{I(i,j)\},\ (i,j) \in \mathcal{N}(x,y)$$

- Gaussian Filter

Smooths the image using a Gaussian kernel.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

$$I'(x,y) = I(x,y) * G(x,y)$$

3.Normalize Pixel Values

Pixel intensities are scaled to the range $[0, 1]$ to stabilize learning.

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$$I_n = \frac{I}{255}$$

4.Train–Test Split

The dataset is divided into training and testing subsets.

$$D = D_{train} \cup D_{test}, D_{train} \cap D_{test} = \emptyset$$

B. Feature Extraction Module

This module converts images into numerical feature vectors.

1. **Color Histogram Features**

Color distribution is captured using histogram bins.

$$H_k = \sum_{(x,y)} \delta(I(x,y) \in bin_k)$$

where $\delta$is the indicator function.

2. **Texture Features**

Texture information is extracted using local patterns and intensity variations.

$$Texture = f(\nabla I, \sigma_I)$$

where $\nabla I$is the gradient magnitude.

3. **Edge Features**

Edges highlight disease boundaries using gradient operators.

$$G = \sqrt{G_x^2 + G_y^2}$$

C.Random Forest Classifier

Random Forest is an ensemble of decision trees.

RF(x)=majority_vote{T1(x),T2(x),…,Tn(x)}

where each $T_i$is a decision tree trained on a random subset of features.

D.Prediction Output

The classifier outputs the predicted disease class along with confidence.

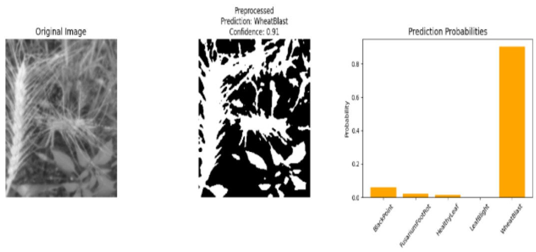
1. **Disease Prediction:**

y^=argmaxP(y∣x)

2. **Confidence Score**

$$Confidence = \max(P(y \mid x))$$

5.3 Prediction result



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IV. RESULT

6.2.1 Training Script

Fig 6.2.1 Training models

6.2.2 Training models Screen

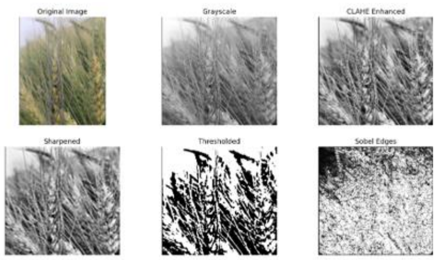

Fig 6.2.2 Training models

6.2.3 Preprocessing models

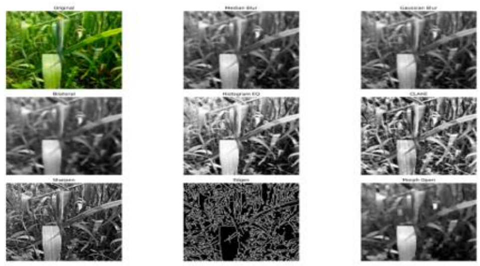

Fig 6.2.3 Preprocessing models

6.2.4 Dashboard

Fig 6.2.4 Dashboard

Fig 6.2.5 Overview

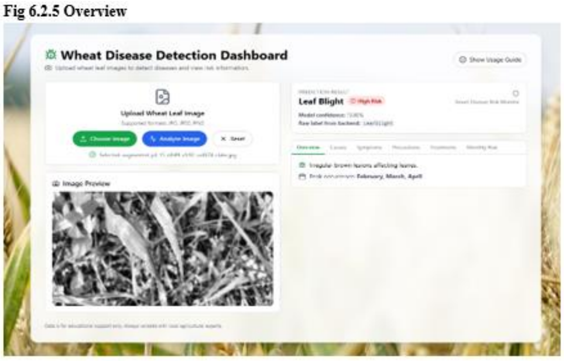

Fig 6.2.5 Overview

Fig 6.2.6 Causes

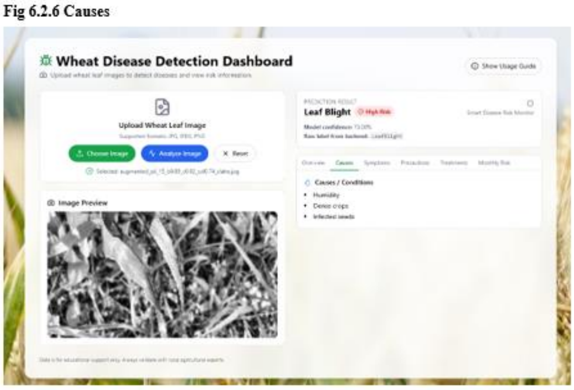

Fig 6.2.6 Causes

Fig 6.2.7 Symptoms

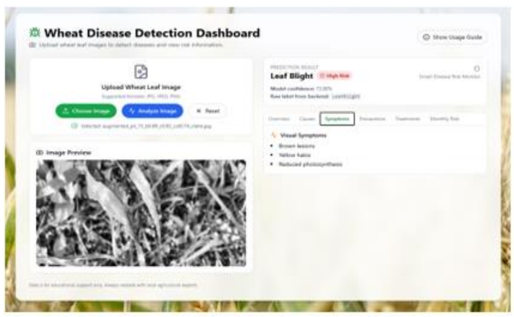

Fig 6.2.7 Symptoms

Fig 6.2.8 Precautions

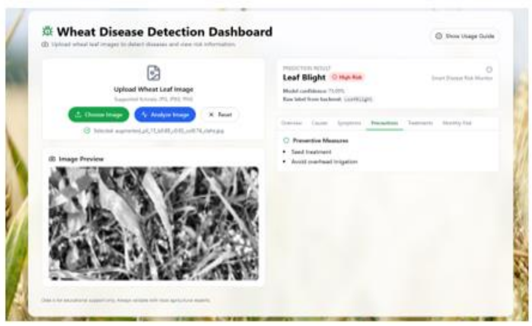

Fig 6.2.8 Precautions

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Fig 6.2.9 Treatments

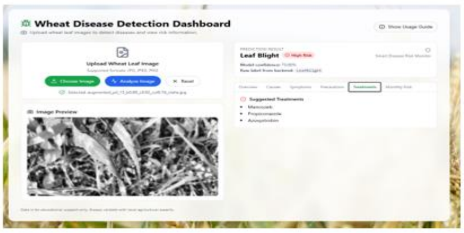

Fig 6.2.9 Treatments

Fig 6.2.10 Monthly Risk

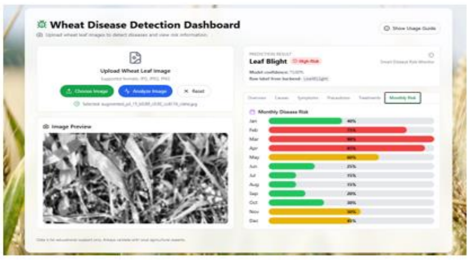

Fig 6.2.10 Monthly Risk

V. RESULTS AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed wheat disease detection system in accurately identifying and classifying multiple wheat leaf diseases. The training phase shows a consistent reduction in loss values across epochs, indicating stable learning and proper convergence of the Random Forest–based classification model. The use of structured preprocessing significantly improved image quality, which directly contributed to better feature discrimination during classification.

The preprocessing results illustrate the impact of different enhancement techniques such as grayscale conversion, CLAHE enhancement, sharpening, thresholding, and edge detection. These transformations helped emphasize disease-specific patterns like spots, discoloration, and texture variations on wheat leaves. Visual comparison of original and processed images confirms that enhanced images provide clearer boundaries and contrast, making them more suitable for feature extraction.

Feature extraction using color and texture-related attributes enabled the model to effectively distinguish between healthy leaves and diseased classes such as Black Point, Fusarium Foot Rot, Leaf Blight, and Wheat Blast. The trained model achieved high validation accuracy, showing strong generalization capability on unseen test data. This indicates that the selected features and classifier are well-suited for wheat disease recognition.

The developed dashboard further validates the practical usability of the system. It displays prediction results along with additional information such as symptoms, causes, precautions, treatments, and monthly risk analysis. This comprehensive output transforms.

VI. CONCLUSION

This project presents an effective machine learning–based approach for automated wheat disease detection using image analysis. The system is designed to support early identification of wheat diseases, helping to reduce crop damage and improve productivity. Image preprocessing techniques such as resizing, noise reduction, and normalization were applied to enhance image quality. Color-based feature extraction using HSV histograms enabled clear differentiation of disease patterns. A Random Forest classifier was trained to categorize wheat leaves into five classes: Black Point, Fusarium Foot Rot, Healthy Leaf, Leaf Blight, and Wheat Blast. The model achieved strong classification accuracy, demonstrating reliable performance on unseen data. The trained model was integrated into a web application using Flask and React for easy interaction. Users can upload images and receive disease predictions with confidence scores. The system also provides information on symptoms, causes, and preventive measures. Overall, the project highlights the potential of machine learning in precision agriculture. It offers a practical, accurate, and scalable solution for sustainable wheat disease management.

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VII. FUTURE WORK

The wheat disease detection system can be further improved by integrating real-time image capture through mobile devices or IoT-based field cameras, enabling instant disease diagnosis directly from farms. Incorporating deep learning models such as CNNs and transfer learning techniques can enhance accuracy and robustness under varying environmental conditions.

Future versions may also include weather and soil data to enable early disease prediction and risk assessment. Expanding the system to support multiple crops and regional languages will increase usability. Deploying the solution on cloud or edge platforms, along with real-world field validation, can improve scalability and bring the system closer to practical agricultural deployment.

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