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Ensemble Machine Learning Approaches for Robust Classification of Maize Plant Leaf Diseases

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ABSTRACT

Maize, a fundamental crop globally, is particularly susceptible to a range of leaf diseases, which can result in substantial yield reductions and economic challenges for agricultural producers. Prompt and precise identification of these diseases is critical to minimizing their adverse effects on food security. This study investigates the application of ensemble machine learning methodologies to improve the robustness and accuracy of maize leaf disease classification. For this proposed experiment, the standard dataset has been utilized, dataset contains 3857 images belonging to blight, Common rust, gray leaf spot, and healthy leafs. By using this dataset three kinds of features (Gray-level co-occurrence matrix (GLCM), Local Binary Pattern (LBP) and Gabor) were extracted. This proposed experiment was carried out in three categories i.e., Single, Double and Multiple combination of features. These extracted features are submitted to three machine learning algorithms, such as s (SVM), kNN, and NN. In single feature Gabor with NN Classifier has given 85.40% as highest accuracy, in the Bi-features Gabor with LBP using NN algorithm has record the 88.00% as an output result, at last in Tri-features (Gabor + GLCM+LB) SVM has raised as a highest recognition accuracy as 88.80%.

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1. INTRODUCTION

Maize, or corn (Zea mays), is one of the most essential staple crops globally, grown in many different regions [1]. It serves as a crucial source of food, animal feed, and raw materials for various industries. The Food and Agriculture Organization (FAO) reports that maize production exceeds 1.2 billion tons each year, making it a key player in ensuring food security, especially in developing countries where it is a primary dietary staple for millions [2]. Unfortunately, maize productivity can be severely impacted by a range of diseases, particularly those that affect its leaves, resulting in significant yield losses. Some of the most common diseases affecting maize include Blight, Gray Leaf Spot (GLS), and Common Rust (CR). If not detected and addressed quickly, these diseases can lead to significant damage. The prompt and precise identification of maize leaf diseases is essential for preventing their proliferation and reducing crop losses [3]. Traditionally, disease identification has depended on visual inspections conducted by farmers or agricultural specialists; however, this approach is susceptible to inaccuracies and inefficiencies, particularly in extensive farming operations. With the advancement of precision agriculture and digital technologies, machine learning has emerged as an effective method for automating disease classification through image analysis. One well-known remedy for this problem is ensemble machine learning techniques. Ensemble approaches produce more reliable and accurate classification results than individual models by utilizing the capabilities of several models [4]. Ensemble learning is particularly well-suited for agricultural applications like the categorization of maize leaf diseases because of its capacity to improve forecast accuracy and efficiently handle complicated, noisy information.

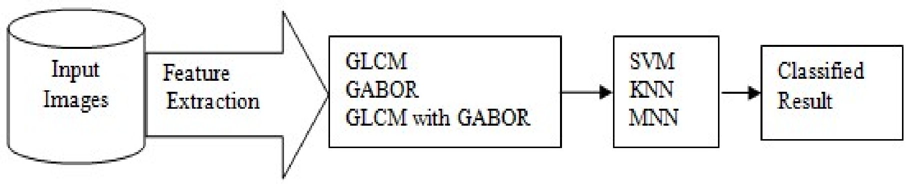


Fig. 1: Block diagram of proposed system.

2. LITERATURE SURVEY

In this area many works have been reported, few of those works few are reported here. Zhang et al. [5] has explored machine learning techniques to classify maize leaf diseases using image data. They applied a combination of Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) for feature extraction and classification, achieving a classification accuracy of over 85% on a small dataset of maize leaf images. Their study highlights the potential of traditional machine learning methods for agricultural disease classification. In a study by Mohanty et al. [6], convolutional neural networks (CNNs) were employed to classify maize leaf diseases using a large dataset of plant images. Their model achieved an accuracy of 98.4%, demonstrating the power of deep learning in automating plant disease classification. This work is considered a benchmark in applying CNNs to agricultural image classification. Ferentinos [7] applied transfer learning using pretrained CNN models such as VGG16 and InceptionV3 for classifying maize leaf diseases. By fine-tuning these pretrained networks, the study achieved an accuracy of 96.3%. Transfer learning proved to be highly effective, especially when training data was limited. Singh and Misra [8] focused on the classification of two major maize leaf diseases, Gray Leaf Spot (GLS) and Northern Corn Leaf Blight (NCLB), using Random Forest and SVM models. Their approach relied on image segmentation and feature extraction, achieving an overall accuracy of 90% in distinguishing between the two diseases.

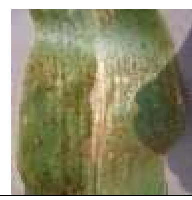
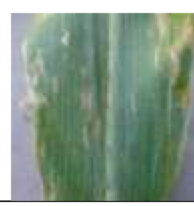
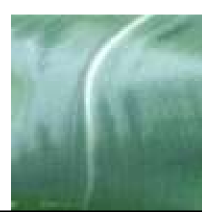
Saberi has implemented ensemble learning methods, including bagging, boosting, and stacking, to classify maize leaf diseases [9]. Their ensemble model, which combined CNN and traditional classifiers, outperformed single models with an accuracy of 94.8%, highlighting the robustness of ensemble approaches. A research paper by authors in [10] proposed a novel system for maize disease detection using drone imagery. The study used CNNs to classify maize diseases in images captured by drones, achieving an accuracy of 93.2%. The use of drone imagery expanded the scope of large-scale monitoring of maize fields. The authors [11] developed a hybrid model that combined traditional image processing techniques (edge detection, color analysis) with deep learning for maize leaf disease classification. Their approach resulted in a classification accuracy of 91.5%, showing that pre-processing can improve the performance of deep learning models. The authors of [12] introduced explainable AI (XAI) methods, such as SHAP (SHapley Additive exPlanations), to interpret CNN-based maize disease classification models. Their study provided insights into how the model made decisions, improving the transparency and trustworthiness of AI systems in agriculture. Because of its vital significance in guaranteeing food security and agricultural production, researchers are paying more and more attention to the classification of diseases that affect the leaves of maize plants. An overview of significant scientific contributions in this field was given by this literature review.

3. MATERIAL AND METHODS

3.1 About Dataset

Figure 1 shows the block diagram of the proposed system. The standard dataset has been utilized for this experiment [13]. The database contains 3857 images, all the images in the uniform size of 224x224. The following Table 1 has the information about the dataset.

Table 1: Details of dataset.

Sl. No.	Dataset	Image	No. of Images
1	Blight		1145
2	Common Rust		1306
3	Gray Leaf Spot		244
4	Healthy		1162
		Total	3857

3.2 Feature Extraction Methods

This experiment has employed the two major and widely used feature extraction methods namely Gabor [14]-[16], GLCM [17], and LBP [18]-[19]. These are popularly used features and widely used techniques.

3.2.1 GLCM (Gray Level Co-Occurrence Matrix)

In image processing, a statistical technique for texture analysis is the Gray-Level Co-Occurrence Matrix (GLCM). By determining how frequently pairs of pixels with gray levels (intensities) occur in each spatial connection (distance and angle), it characterizes the spatial relationship between pixels in a grayscale image. Numerous texture properties, including contrast, correlation, energy, and homogeneity, can be extracted using the GLCM. These features are useful for tasks including pattern identification, medical image analysis, remote sensing, and agricultural diagnostics. The GLCM contains a variety of features i.e., Contrast, Correlation, Energy, Homogeneity.

Contrast: Contrast measures the intensity variation between a pixel and its neighboring pixel across the whole image and is given by (1).

$$Contrast = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i-j)^2.M(i,j) \tag{1}$$

In (1), G is the number of gray levels and M (i, j) is the normalized GLCM value for gray levels i and j.

Correlation: The degree of correlation between a pixel and its neighbouring pixel is measured by correlation, given by (2) and it displays the linear relationship between adjacent pixels' gray levels.

$$Correlation = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{(i-\mu_i(j-\mu_j).M(i,j)}{\sigma_i\sigma_j} \tag{2}$$

In (2):

μ_i and μ_j are the means of gray levels i and j, respectively.

σ_i and σ_j are the standard deviations of gray levels i and j.

Energy: Energy, sometimes referred to as Angular Second Moment (ASM), gauges how consistent or smooth an image's texture. Higher values indicate greater consistency or repetition in the texture pattern. It represents the distribution of pixel intensity levels. The equation (3) indicates energy.

$$Energy = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}M(i,j)^2 \tag{3}$$

Homogeneity: Inverse Difference Moment (IDM), another name for homogeneity, quantifies how closely the distribution of components in the GLCM resembles its diagonal. When pixel pairs with comparable brightness occur more frequently, as indicated by high homogeneity values, the texture is more uniform. It is indicated by (4).

$$Homogeneit\ \ y = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{M(i,j)}{1+|i-j|} \tag{4}$$

3.2.2 Gabor

Gabor features are texture descriptors frequently applied in image processing and pattern recognition. These features are based on Gabor filters, which are specific filters designed to capture both frequency and orientation details from an image. Gabor filters function by examining an image at various scales and orientations, simulating how the human visual system detects textures and edges. Following (5) is the formula of Gabor.

$$\begin{aligned} G_c[i,j] &= Be\frac{(i^2+j^2)}{2\sigma^2}\cos(2\pi f(i\cos\theta + j\sin\theta)) \\ G_s[i,j] &= Ce\frac{(i^2+j^2)}{2\sigma^2}\sin(2\pi f(i\cos\theta + j\sin\theta)) \end{aligned} \tag{5}$$

3.2.3 LBP (Local Binary Pattern)

This method is an effective and straightforward approach for texture analysis in images. The process involves comparing a pixel in the image to its surrounding pixels and generating a binary code based on this comparison. This code represents the texture in the immediate area of the pixel. Through this method, LBP captures important texture details, making it a useful tool for various tasks like image classification and facial recognition. Following (6) is the formula for LBP.

$$LBP_{P.R} = \sum_{p=0}^{P-1} S(g_p - g_c)2^p \tag{6}$$

$$s(x) = \begin{cases} 1, if\ x \geq 0; \\ 0, otherwise \end{cases} \tag{7}$$

4. Results with Discussion

This experiment has been carried out on a maze plant diseased with healthy leaf dataset, the dataset contains 3857 images. On these images the GLCM, LBP, and Gabor methods were applied, and features are extracted. These features were given as an input to three widely used machine learning algorithms known as KNN [20]-[21], SVM [22], and NN (Neural Network) [23]. Following Tables [2], [3], and [4] show the performance of the proposed algorithm and categorical experiment result. Table 2 shows the single feature result for GLCM, Gabor, and LBP.

Table 2: Single feature result.

Sl.No.	Feature	Classifier	Result
1	GLCM	NN	87.80%
2	Gabor	NN	89.40%
3	LBP	NN	90.90%

Table 3: Bi-features result.

Sl.No.	Feature	Classifier	Result
1	Gabor with GLCM	NN	89.20%
2	Gabor with LBP	NN	96.00%
3	GLCM with LBP	NN	90.20%

Table 4: Tri-features result.

Sl.No.	Feature	Classifier	Result
1	Gabor, GLCM, LBP	SVM	98.80%

From Tables 3 and 4 is seen that from single to tri-features the results are increasing, and this is the main advantage of ensemble features. Figure 2 shows all features have reported the highest result.

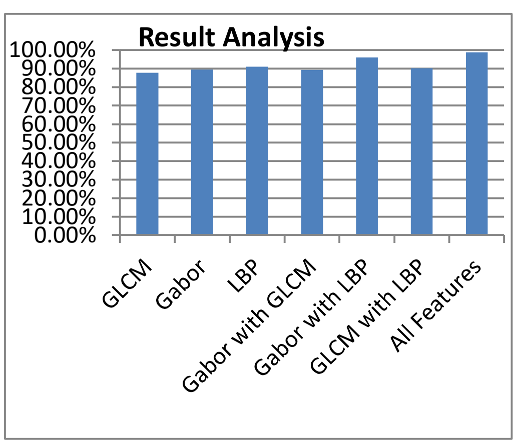


Fig. 2: Result analysis of the proposed method.

From Tables 3 and 4 is seen that from single to tri-features the results are increasing, and this is the main advantage of ensemble features. Figure 2 shows all features have reported the highest result.

5. CONCLUSION

Early detection of leaf diseases of maize leaf is crucial for the farmers to take precautionary measures to save the time and energy of farmers. This proposed experiment is put an effort to give solution to the farmers problems by ensemble the variety of texture features alongwith with different classifiers. This experiment has given the highest 98.80% recognition accuracy. In the future work effort to collect much more dataset and developing a robust method to gain highest recognition accuracy.

The machine learning approach is widely used in critical research areas such as medical [24]-[25] and other complex problems in various domains [26]-[29].

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