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RESEARCH ARTICLE

Maize Leaf Disease Classification Using a Hybrid Framework Integrated with Color and CNN-Derived Features

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Abstract

Early recognition of maize leaf disorders and applying precautionary measures on time may help to increase the yield and quality. This study introduces an architecture for the recognition and categorization of maize leaf diseases based on the deep Inception-v3 and maximum value-based color features. The core steps of the designed framework include data acquisition, feature extraction, fusion, and classification. The maize leaf image dataset is utilized, which is publicly available on Kaggle, comprising four classes. The deep learning features are collected by applying the transfer learning approach to the pre-trained Inception-v3 model. In addition to the deep features, maximum value-based color features are computed from RGB, HSV, and LAB color spaces. After that, both deep and color attributes are merged using a serial-based strategy. Finally, the fused vector is fed to the various machine learning classifiers for the recognition of disorders. The designed approach achieves an accuracy of 99% on the Ensemble Subspace Discriminant (ESD) classifier. The results showed that the proposed approach achieved promising disease recognition performance.

Keywords: maize leaf, disease classification, plant disease, deep learning, color features, features fusion.

1 Introduction

The maize crop is a versatile agricultural product and one of the most utilized crops. Maize or corn, also known as *Zea mays* L., can grow under varying weather conditions. After wheat and rice, it is considered the third-largest farming product. Maize is the second most popular cereal crop, and thus it is also called the "Queen of Cereals". It comprises starch, protein, fat, and energy density of 79.95%, 10.11%, 4.19%, and 3365 Kcal/Kg, respectively [1].

The maize crop can be affected by many diseases, which lead to a decrease in production and economic loss. Most diseases in maize leaves include blight, gray leaf spot, brown spot, common rust, and dwarf mosaic [2]. In China, due to diseases, the annual maize loss reaches 6% to 10% [3]. In the early stages, these diseases seem similar; therefore, it is difficult to recognize healthy and different diseases with the

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naked eye. The visual inspection requires continuous monitoring and a team of agriculture experts for the identification of maize leaf disorders [4]. Therefore, this is an expensive, lengthy, and insufficient method. This is also less reliable because a chance of error is present, and proper precautionary measures are not adopted on time. If diseases are not recognized at an initial phase, it can decrease the production of maize.

To overcome the problems faced in maize leaf disease recognition, computer vision and image processing techniques can be utilized [5]. Using these methods, automated models were developed to identify diseases from leaf images. In an automated recognition system, multiple features are taken from the maize leaf images and given to the machine learning algorithms for accurate classification into the relevant category [6]. The extraction of robust features determines the success of the disease recognition model. The most utilized features for the recognition of plant leaf diseases include color, shape [7], texture [8], and their derivatives [9].

Nowadays, deep learning is broadly utilized by researchers for several recognition and categorization tasks such as object classification [10], biometrics [11], and agriculture [12, 13]. This is a sub-field of machine learning, which consists of convolutional neural networks (CNNs) and automatically extracts powerful features at pixel level and layer by layer. In studies [14–16], authors used CNNs for maize disease detection and identification. Combining deep and handcrafted features can also help enhance the results for plant disease classification [17, 18].

In this work, a technique is presented for maize leaf disorder categorization. The designed technique is assessed on four classes of maize leaves dataset, publicly available on Kaggle. The four classes of data include gray leaf spot, common rust, blight, and healthy. The contributions of this study are as follows:

- Deep transfer learning approach is employed using Inception-v3 for deep feature extraction. The last prediction layers of the pretrained model are removed and a new dense layer is added, which gives 1000 features. These features help in identifying complex disease patterns.
- Three color spaces, including RGB, LAB, and HSV, are utilized to compute features. Then the top value 500 color features are extracted, which highlight the important color changes between the diseased and healthy regions.
- Both deep and color features are serially concatenated and provided to various classifiers for the recognition of diseases.

The rest of the sections of this article are structured in the following sequence: Section 2 describes the existing work on maize leaf disease identification. The developed framework is presented in Section 3 with the help of visuals and mathematical formulation. The results and their discussion are provided in Section 4. At the end, Section 5 concludes this study, and possible future directions are suggested.

2 Related Work

The maize leaf disorder recognition consists of a number of steps, including preprocessing, feature extraction using deep learning [19] models, feature optimization [20, 21], fusion [22], and classification [23, 24]. Recently, researchers have introduced approaches for the recognition of maize leaf disorders. Some studies are reviewed to analyze the previous work. Aravind et al. [25] obtained the statistical histogram-based attributes and a bag of features for disease categorization. The taken attributes were fed to the multiclass SVM. The proposed technique obtained an average recognition rate of 83.7% using the bag of features and 81.3% on the combined statistical features. They tested their technique using 2000 samples taken from the publicly available PlantVillage database. In [26], researchers suggested a CNN-based method to discover maize leaf disorders. In the preprocessing step, they enhanced the image feature using the PCA whitening algorithm. After that, they trained the modified LeNet model [27] on four classes of maize leaves images. The proposed model achieved a maximum recognition rate of 97.89%. Setiawan et al. [5] define a deep learning model for maize disease categorization. They conduct experiments and compared two CNN models AlexNet [28] and SqueezeNet [29]. They also optimize the network using SGDM. The method was evaluated using four classes of maize leaf images i.e., rust, spot, blight, and healthy taken from the PlantVillage database. They achieved 97.69% accuracy on the AlexNet model and 44.49% accuracy on SqueezeNet.

Researchers in [15] utilized two CNN architectures, AlexNet and ResNet-50. They performed experiments on 405 leaf images of a privately collected dataset. They obtained the best accuracy using the ResNet-50 model, which is 98.18%. The best accuracy is achieved when the training and testing ratios are set at 70% and 30%, respectively. Malliga et al. [4] presented a CNN-driven maize leaf disorder classification model. They performed classification with the help of the AlexNet architecture and achieved a maximum accuracy of 98.5%. Zeng et al. [3] designed a SKPSNet-50 architecture by replacing the 3×3 convolutional kernel with Select Kernel-Point-Swish_B. This is the enhanced core component of the chosen kernel and improves the ability of the architecture. The proposed SKPSNet-50 model achieved a recognition rate of 92.9%. In [1], researchers applied the transfer learning approach to recognize maize leaf diseases. They utilized the AlexNet architecture for transfer learning and obtained an accuracy of 99.16%. The designed approach was assessed on two categories of maize diseases. One category consists of 1363 images, and the other contains 929 images. Baldota et al. [30] utilized the transfer learning approach for the classification of maize leaf diseases. They employed transfer learning on the DenseNet-121 model, and achieved a promising accuracy of 98.45%.

Researchers in [31], collected their maize leaf data for the identification of diseases. They utilized the deep Inception-v3 network for training purposes. After extensive experiments, they obtained an overall recognition rate of 95.99%. A mobile application developed based on the VGG16 model [32]. The VGG16 model achieved 95% test accuracy on a four-class dataset of maize leaf diseases. A hybrid model was designed that integrates the MobileNetV2 and vision transformer for the classification of maize leaf diseases [33]. Furthermore, explainable AI is incorporated into the model for more accurate decision-making. A multi-scale convolutional pooling network [34] was proposed that utilized the MobileNetV2 as a backbone with the PoolFormer block. After extensive experimentation, the model achieved 97.44% recognition rate. A CNN model [35] named MaizeNet was introduced to enhance the disease classification results. The MaizeNet utilized an attention mechanism that addresses the vanishing gradient issue and improves the training process. The MaizeNet achieved 95.95% classification accuracy on the maize leaf images dataset. ResNet152V2 architecture [36] proposed to identify the healthy and diseased images, and achieved 97% accuracy. Researchers developed Shuffle Attention Max Network (SA-MaxNet) [37] for disease classification in Internet of Things (IoT) environments. Extensive experimentation was conducted, and SA-MaxNet obtained 95.99% classification accuracy.

The application of ML and DL for the identification of plant diseases in maize exhibits several limitations across the reviewed works. The majority of research, including those that use CNN variations (SKPSNet-50, AlexNet, SqueezeNet, and VGG16), mostly rely on limited, domain-specific, or lab-curated datasets, which restricts generalization to real-world scenarios with widely varying background noise, lighting, and image quality. Many models exhibit excellent accuracy in controlled situations but have issues with resilience and scalability when used in the field, particularly in contexts with limited resources or mobility. Broader application is further hampered by problems like class imbalance, overfitting, and a lack of variation in disease categories. Another issue is computational expense, since lightweight models frequently compromise accuracy, and some architectures are too resource-intensive for realistic agricultural adoption. Additionally, the majority of methods are not interpretable and do not incorporate multimodal data, such as temporal or environmental aspects, which could increase the dependability of predictions. The bulk of research falls short of thorough cross-validation, benchmarking against standardized datasets, or deployment-ready evaluations, despite the promising nature of transfer learning and optimization approaches. This leaves a gap between experimental performance and real-world usefulness.

3 Proposed Methodology

In this segment, the designed maize leaf disease recognition and classification framework is presented. The sequence of the designed methodology is presented in Figure 1. The significant phases of the designed framework include dataset collection, extraction of features that include maximum value-based color features, and deep Inception-v3 [38] features. After feature extraction, features are fused with the help of a serial-based concatenation technique. At the final stage, the fused feature vector is fed to the various classifiers for disease classification.

3.1 Dataset Description

A publicly accessible dataset of maize leaf images is utilized to assess the proposed technique. The data is available on Kaggle and was created using two famous datasets, PlantDoc [39] and PlantVillage [40]. The dataset consists of four classes that are blight, common rust, healthy, and gray leaf spot. The blight class

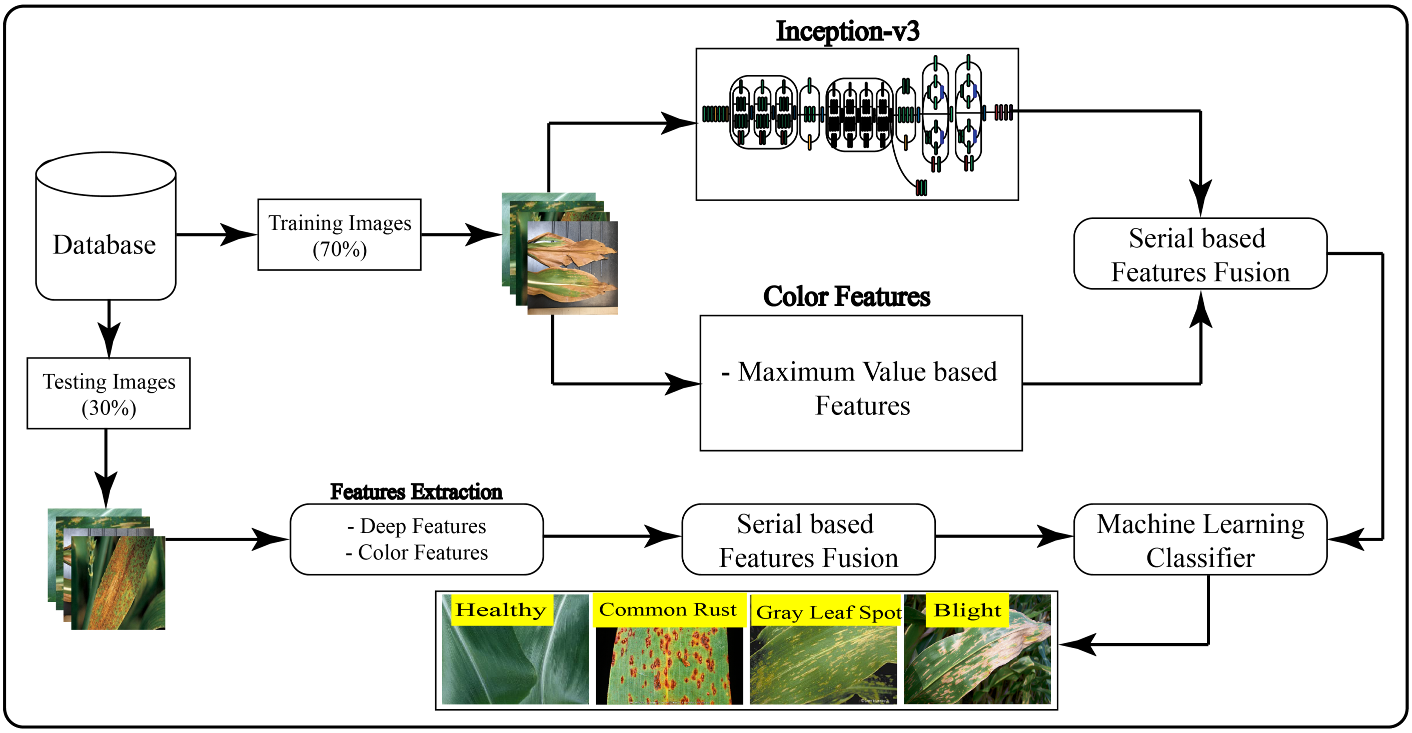

Figure 1. The proposed framework for maize leaf disease classification.

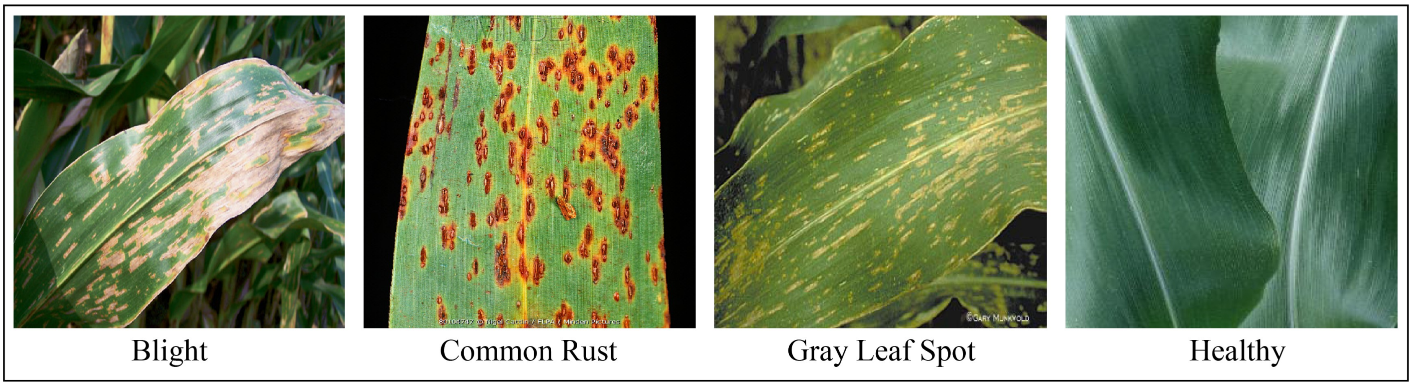

Figure 2. Sample of maize leaves of the selected database.

contains 1146 samples, common rust consists of 1306 samples, the gray leaf spot consists of 574 samples, and the healthy class consists of 1162 samples. The diseased images of the selected database are shown in Figure 2. In the presented experiments, the dataset was divided into 70% for training purposes and 30% for the testing phase.

3.2 Feature Extraction

In this work, we extracted color features and deep features. Color features are extracted using three color spaces, such as RGB, HSV, and LAB. The deep features are obtained from the pre-trained Inception-v3 architecture using the transfer learning technique. A detailed description of the feature extraction phase is presented below.

3.2.1 Maximum Value-based Color Features

In this work, RGB, LAB, and HSV color spaces are used for color feature extraction. Figure 3 represents the RGB color spaces of all four classes and their respective HSV and LAB color transformations. Initially, all channels of these three-color spaces are separated and converted into a histogram. Then, different statistical parameters like mean (m), skewness (s), variance (v), standard deviation (sd), and kurtosis (k) are calculated for all nine channels. The calculated parameters are serially combined to get a feature vector $cv(i)$ of dimension $N \times 9500$. Here, N shows the total sum of training images. To compute the robust color features, the vector is sorted in a descending manner, and select features which are having maximum values. This process eliminates the irrelevant features and results in maximum value-based color features. This can be mathematically described as:

$$cv1_{RGB}(i) = \{m, sd, v, k, s\}_{i=1}^{5} \tag{1}$$
$$cv2_{HSV}(i) = \{m, sd, v, k, s\}_{i=1}^{5} \tag{2}$$
$$cv3_{LAB}(i) = \{m, sd, v, k, s\}_{i=1}^{5} \tag{3}$$
$$cv(i) = cv1_{RGB}(i) + cv2_{HSV}(i) + cv3_{LAB}(i) \tag{4}$$
$$s_{cv}(i) = \text{descending}(cv(i)) \tag{5}$$

where $s_{cv}(i)$ is the color feature vector in a descending manner. The first 500 features of this feature vector are utilized.

$$\psi(CF) = \{s_{cv}(i)\}_{1}^{500} \tag{6}$$

$\psi(CF)$ is the significant color attribute set of size $N \times 500$ having maximum values.

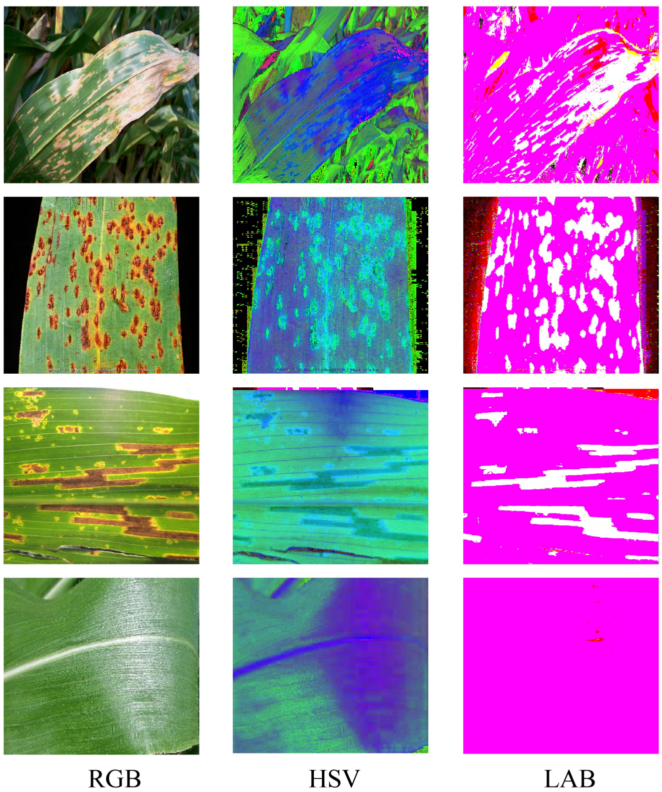

Figure 3. Color spaces utilized for feature computation.

3.2.2 *Deep Learning Features*

Inception-v3: The pre-trained Inception-v3 model [38] consists of a directed acyclic graph architecture. To extract features from this network, several filters are implemented on different layers. This framework is flexible enough to apply different parameters and filter sizes on the same layer. The inception-v3 network consists of 316 layers, including 94 convolutional layers, and 350 connections. The image input size for Inception-v3 is 299×299×3. The model was trained on the challenging large ImageNet database [41], having 1000 classes and more than a million images. In this approach, this model is utilized for the categorization of maize leaf disorders. For feature extraction, the deep transfer learning approach is utilized. During this process, the last prediction layers of the Inception-v3 model were removed. Then a new dense layer of size 1000 is added, and activations are performed, and a feature vector of dimension N×1000 is obtained. The model architecture is conferred in Figure 4.

3.3 Features Fusion

After feature extraction, all features are merged in a singular feature vector with the help of a serial-based concatenation approach. Two feature vectors, including color features and deep Inception-v3 features, are fused to achieve a single feature vector of size $N \times 1500$. This process is presented in Figure 5, and mathematically described as:

$$\delta(FV) = \delta(CF)_{N\times 500} + \delta(DF)_{N\times 1000} \tag{7}$$

where $\delta(CF)_{N\times 500}$ and $\delta(DF)_{N\times 1000}$ denotes the maximum value-based robust color features, and deep Inception-v3 features, while $\delta(FV)$ is the final merged feature vector. This vector is then fed to several classifiers for the final recognition process.

4 Experimental Setup and Results

This section presents a comprehensive description of the experimental outcomes. The designed approach is also analyzed and compared with the existing methods. All evaluations are conducted using MATLAB R2023b on a 12^{th}-generation Core i7 desktop system with a 3.6GHz processor and 32 GB RAM. To evaluate the proposed framework, a publicly available maize leaf image dataset is utilized. The selected dataset contains a total of four classes. To collect the classification results, Holdout cross-validation is employed. This approach splits the data for training and testing. 70% of the data is used for training, and 30% held out for testing purposes. Various performance measures are used to validate the effectiveness of the model, including accuracy (Acc), F1-score (F1-S), computational time, precision (Pr), and recall (Rc).

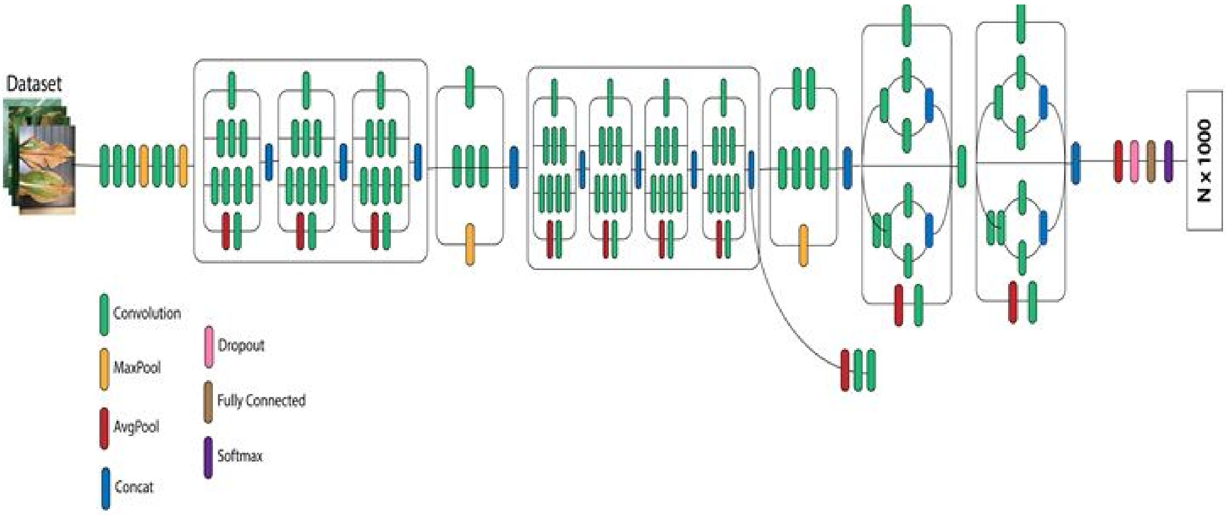

Figure 4. Framework of the Inception-v3 model for deep feature extraction.

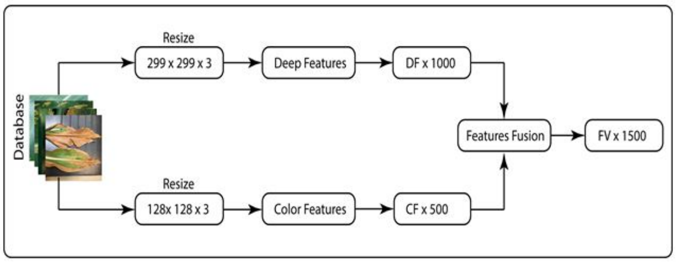

Figure 5. Feature fusion process of the proposed framework.

4.1 Results

This section presents various experiments as presented in Table 1 to collect the classification results. In experiment 1, only deep features are extracted and given to the classifiers for disease recognition. The feature vector size in experiment 1 is $N \times 1000$. Experiment 2 was performed using 1000 deep features and 1000 maximum value-based color features. The feature vector of size $N \times 2000$ is given to the classifiers in the recognition phase. In experiment 3, 1000 deep features and 500 robust color features based on maximum value are fused, and a feature vector of size $N \times 1500$ is given to classifiers for classification.

Table 1. Experimental setup for feature combinations.

Experiment	Feature Description
Experiment 1	Deep Inception-v3 features ($N \times 1000$)
Experiment 2	Deep Inception-v3 and 1000 Color features ($N \times 2000$)
Experiment 3	Deep Inception-v3 and 500 Color features ($N \times 1500$)

4.1.1 *Numerical Results: Experiment 1*

The first experiment utilized only deep Inception-v3 features, and a N×1000 feature vector is fed to the classifiers. The classification is performed using several machine learning algorithms, but prominent performance is achieved on Cosine K-Nearest Neighbor (C-KNN), Quadratic SVM (Q-SVM), Cubic SVM (C-SVM), Linear Discriminant (LD), Medium Gaussian SVM (MG-SVM), Linear SVM (L-SVM), and Ensemble Subspace Discriminant (ESD). All results of experiment 1 are presented in Table 2. The maximum accuracy of 92.9% is achieved on the ESD classifier. The computational time for the ESD classifier is 84.38 seconds. Other measures computed on the ESD classifier are precision 87.5%, recall 87.5%, and F1-score 87.5%. The performance of the ESD classifier can be validated from the confusion matrix given in Figure 6. The best computational time is 13.13 seconds (sec) achieved on the LD classifier with 91.8% accuracy. The computational time comparison of all classifiers is also presented in Figure 7.

4.1.2 *Numerical Results: Experiment 2*

In experiment 2, deep features and color features are combined, which gives the vector size of N×2000. The 1000 fused deep features and 1000 color features perform the recognition process. After performing classification using several classifiers, promising performance is achieved on the fine tree, medium tree, coarse tree, ensemble bagged tree (EBT), ensemble subspace discriminant (ESD), and ensemble subspace KNN (ES-KNN), and ensemble RUSboosted tree (ERT) classifiers. Table 3 presents the classification results collected on the selected classifiers. The classification time of selected classifiers is also

Table 2. Classification outcomes of experiment 1.

Classifier	Acc (%)	Pr (%)	Rc (%)	F1-S (%)	Time (sec)
C-KNN	88.80	84.75	87.00	85.25	14.69
LD	91.80	89.50	89.75	89.75	13.13
MG-SVM	92.20	89.00	91.50	89.75	28.67
L-SVM	91.90	89.00	90.50	89.75	26.26
Q-SVM	92.00	89.25	90.25	89.75	21.33
C-SVM	92.10	89.50	90.00	90.00	24.45
ESD	**92.90**	87.50	87.50	87.50	84.38

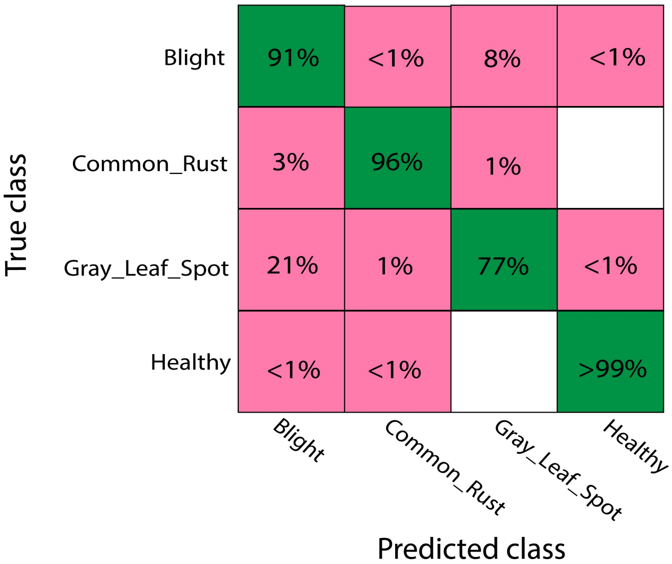

Figure 6. Confusion matrix of the ESD classifier for experiment 1.

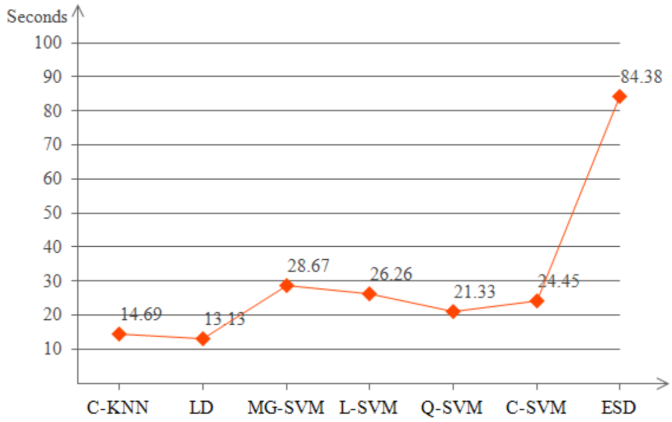

Figure 7. Computational time comparison of classifiers in experiment 1.

compared in Figure 9. The highest accuracy achieved in this experiment is 98.9%, which is computed on EBT, ESD, and ES-KNN classifiers. The computational time for EBT, ESD, and ES-KNN classifiers is 38.57 sec, 99.05 sec, and 198.34 sec, respectively. The confusion matrix of the ESD classifier is given in Figure 8 to validate the classification results. The best computational time is 13.33 seconds, provided by the medium tree. The calculated classification accuracy on the medium tree is 97.8%.

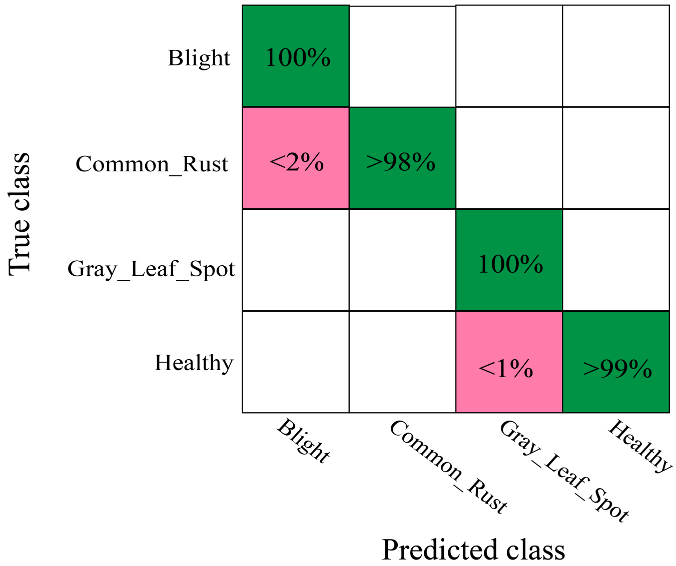

Figure 8. Confusion matrix of the ESD classifier for experiment 2.

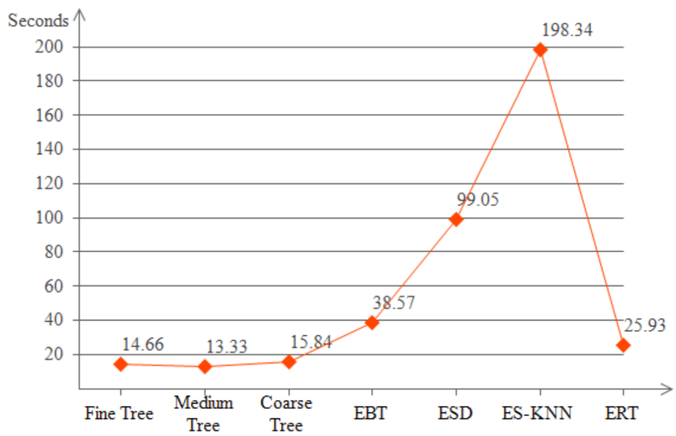

Figure 9. Computational time comparison of classifiers in experiment 2.

4.1.3 *Numerical Results: Experiment 3*

In the last experiment 3, the feature vector N×1500 is formed using 1000 deep features and 500 color

Table 3. Classification results of experiment 2.

Classifier	Acc (%)	Pr (%)	Rc (%)	F1-S (%)	Time (sec)
Fine Tree	97.80	97.95	98.87	98.81	14.66
Medium Tree	97.80	97.83	98.80	98.89	13.33
Coarse Tree	97.80	99.77	98.70	99.23	15.84
EBT	**98.90**	99.80	99.95	99.93	38.57
ESD	**98.90**	99.80	99.92	99.85	99.05
ES-KNN	**98.90**	99.80	98.99	99.39	198.34
ERT	93.00	92.50	95.50	94.75	25.93

features. The achieved maximum accuracy is 99% on the ESD classifier. Other performance measures are also obtained, 99% for each one, as presented in Table 4. The effectiveness of the ESD classifier can be confirmed through the confusion matrix given in Figure 10. The computational time for the ESD classifier is 46.04 seconds. The best computational time is 12.04 seconds, calculated on the medium tree classifier with 98.8% accuracy. It is to be noted that on other classifiers, good performance is also obtained. The 98.8% accuracy is also obtained on EBT, ES-KNN, and ERT with the computational time of 26.39 sec, 171.86 sec, and 23.76 sec, respectively. The computation time of all selected classifiers is also compared in Figure 11.

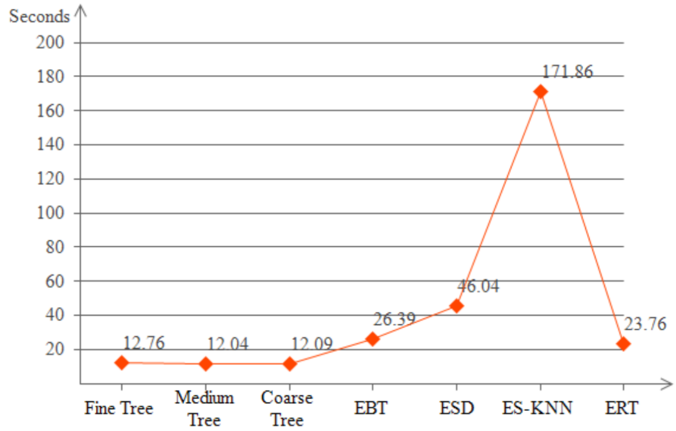

Figure 11. Computational time comparison of classifiers in experiment 3.

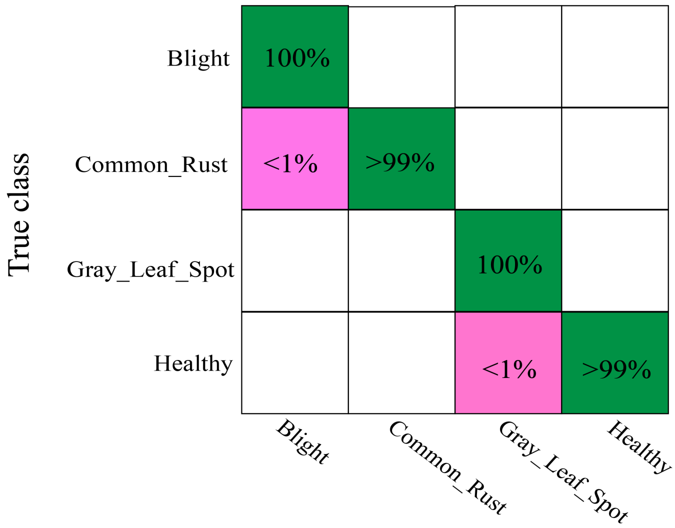

Figure 10. Confusion matrix of the ESD classifier for experiment 3.

4.2 Discussion and Analysis

In this work, a significant technique for the detection and classification of maize leaf diseases is proposed. The proposed technique extracts the deep Inception-v3 features and maximum value-based robust color features. Three experiments are conducted to collect the results. In the first experiment, only deep features are utilized to classify the diseases. In this experiment, the maximum accuracy achieved on the ESD classifier is 92.9%. The ESD took more computational time compared to other classifiers in this experiment. The computational time for ESD is 84.38 sec, which is the highest among all classifiers in experiment 1. In experiment 2, 1000 color features were combined with deep features to calculate the results. The highest observed classification is an accuracy of 98.9% on three classifiers EBT, ESD, and ES-KNN. The computational time for EBT, ESD, and ES-KNN is 38.57 sec, 99.05 sec, and 198.34 sec, respectively. Thus, here the classification accuracy is improved by combining the color features with deep Inception-v3 features. But learning time is increased. In the third experiment, we reduced the color feature size and fused 500 color features with Inception-v3 features. We obtained a maximum recognition rate of 99% on the ESD classifier. The computational time for ESD is 46.04 sec. The promising accuracy of 98.8% is achieved on EBT, ES-KNN, and ERT classifiers. The computational time for EBT, ES-KNN, and ERT is 26.39 sec, 171.86 sec, and 23.76 sec, respectively. The comparison of classification accuracy and classification computational time of the ESD classifier is presented in Figures 12 and 13, respectively.

Table 4. Classification results of experiment 3.

Classifier	Acc (%)	Pr (%)	Rc (%)	F1-S (%)	Time (sec)
Fine Tree	98.80	98.70	98.80	98.87	12.76
Medium Tree	98.80	98.80	98.90	98.90	12.04
Coarse Tree	98.80	98.90	98.90	98.90	12.09
EBT	98.80	98.70	98.80	98.91	26.39
ESD	99.00	99.00	99.00	99.00	46.04
ES-KNN	98.80	98.80	99.85	99.32	171.86
ERT	98.80	98.90	99.99	99.44	23.76

Table 5. Quantitative results comparison with existing methods.

Ref.	Year	Model	Accuracy (%)
[30]	2021	DenseNet-121	98.45
[3]	2022	SKPSNet-50	92.90
[31]	2022	Inception-v3	95.99
[42]	2023	ResNet-50	95.59
[43]	2024	ShuffleNetV2 + MP + SAM	98.40
[32]	2025	VGG16	95.00
[34]	2025	MobileNetV2 + PoolFormer block	97.44
[35]	2025	MaizeNet	95.95
[44]	2025	VGG16	95.16
[36]	2026	ResNet152V2	97.00
[37]	2026	SA-MaxNet	95.99
Proposed	–	**Inception-v3 + Color Features**	**99.00**

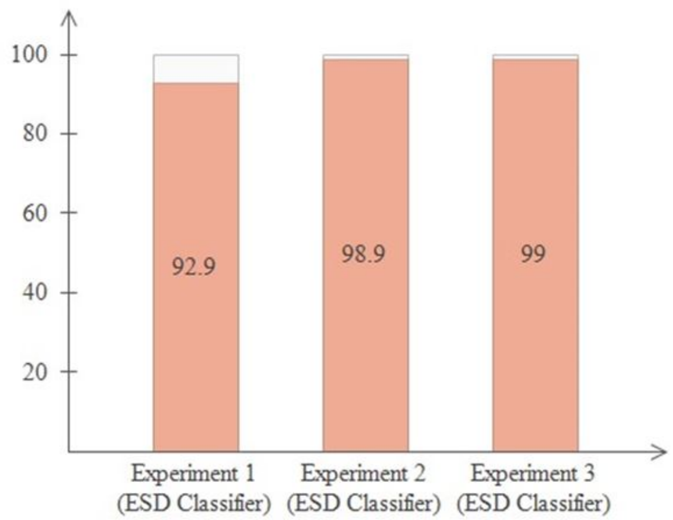

Figure 12. Comparison of classification accuracy obtained on ESD classifier in performed experiments.

It is observed from the above discussion that color features combined with deep features produce good results. In the second and third experiments, two different vector sizes of color features are utilized. After decreasing the color features in experiment 3, the accuracy is enhanced, and computational time is also reduced. With 1000 color features in experiment 2, the obtained accuracy is 98.9% on the ESD classifier with 99.05 s computational time. In experiment 3, 500 color features are utilized and obtained 99% accuracy on the ESD classifier with 46.04 s computational time. Using only 500 color features, the accuracy is enhanced, while the computational time is also reduced.

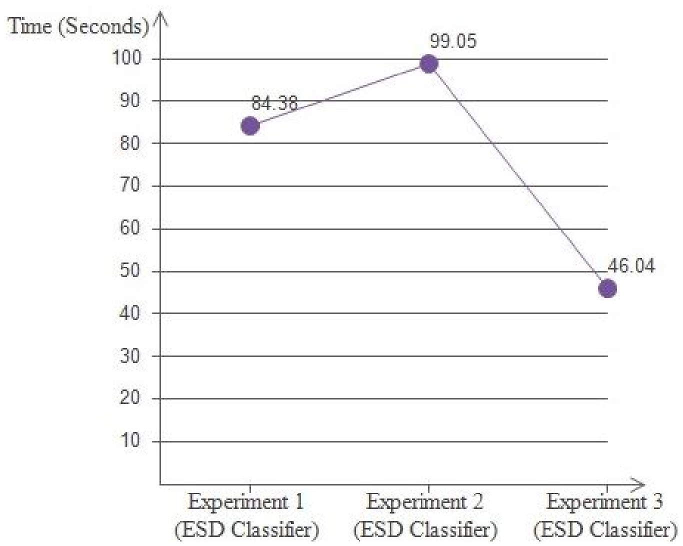

Figure 13. Comparison of computational time of the ESD classifier in performed experiments.

A comparison of the designed approach with existing methods is also presented in Table 5. In previous studies, researchers designed their models based on deep learning networks. In this study, a method is presented that utilizes the deep Inception-v3 features and maximum value-based robust color features. Our proposed model outperforms the previous techniques and achieves a recognition rate of 99% for maize leaf disease categorization.

There are certain limitations associated with this model since it largely relies on the quality and quantity of data fed into it. Considering that it utilizes inception v3 with color-based hand-crafted features, it might need high computational power and is therefore not appropriate for cost-effective, real-time, on-field application. It may also find it hard to work effectively in uncontrolled scenarios where lighting, background, and orientation play a significant role. It is also important to note that this model categorizes selective diseases and not their intensity.

5 Conclusion and Future Work

In this study, a new technique is introduced to recognize and classify maize leaf disorders. The designed technique extracts Inception-v3 features and color features. After the extraction of features, the robust color features based on the maximum value were selected, and these features were combined with deep features. The merged vector is then fed to the machine learning classifiers for the final recognition process. Several experiments were performed for the recognition of maize leaf disorders, and a maximum recognition rate of 99% was obtained on the ESD classifier. It is concluded after the experiments that the color features help in enhancing the classification accuracy. The accuracy of the designed method is increased after decreasing the color attributes, which also decreases the training time of classifiers. In the future, the aim is to propose more significant techniques for more complex data having more classes. The introduced maximum value-based color features can also be combined with other deep networks for extensive experiments.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

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Ethical Approval and Consent to Participate

Not applicable.

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