Corn Leaf Disease Identification via Transfer Learning: A Comprehensive Web-Based Solution

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Abstract: Effective crop disease prevention is essential to ensure global food security, and early disease detection is a vital part of this protection. Traditional techniques of identifying disease are lengthy process, costly, sometimes require specialized knowledge, and nevertheless may produce erroneous outcomes. Artificial intelligence offers the best answer in this situation. Deep learning has become essential for analyzing images and classification. This study proposes a website that uses deep learning for classifying three major diseases of maize leaves: blight, common rust, grey leaf spot, as well as for identifying healthy leaves. Additionally, it conducts a comparative analysis of various state-of-the-art models using the same dataset to determine the most suitable approach for website development, considering metrics such as accuracy, precision, recall, F1-score, training time, and model size. All the used models (MobileNetV2, AlexNet, ResNet18, VGG16, VGG19, and SqueezeNet) have been optimized for faster operation and lower storage consumption. The models were trained using the "Corn or Maize Leaf Disease Dataset" on Kaggle, which included 2930 images of maize leaves. After that the models were tested using a separate set of 422 images, categorized into four classes: three representing diseases (blight, common rust, and grey leaf spot) and the fourth representing healthy leaves. Out of all the models, ResNet18 has the highest accuracy (96.45%). ResNet18 has several evaluation matrices that make it ideal for this investigation, including quick training and a small model size. As ResNet18 provides the best result, the website can accurately classify disease class and display the probability of identification for uploaded corn leaf images using this model. The model's performance is found satisfactory for its real-world application in automatically detecting maize leaf diseases.

Keywords: Machine Learning, Deep Learning, Transfer Learning, MobileNetV2, AlexNet, ResNet18, VGG16, VGG19, SqueezeNet, Corn Disease Classification, Web based prediction system.

1 Introduction

The agricultural crop maize, or corn, is very versatile and can grow in a variety of agro-climatic situations. Following wheat and rice, it is the third most important crop in terms of agribusiness. Because maize is the cereal that is most often grown worldwide, it has earned the title "Queen of Cereals." It contributes significantly to ensure food security by providing an essential supply of food, nutrition and energy for the expanding world population [1]. Maize is also a major supplier of raw materials for a variety of industrial goods.

Though the maize plant has a remarkable yield potential, it is highly susceptible to a number of diseases that can cause yearly losses of 6% to 10% [2], [3]. These maize diseases are largely brought on by different bacteria, fungus, viruses, and viroids. Discoloration, rot, scab, blight, necrosis, wilt, and deformities are typical signs that are used to recognize and diagnose foliar diseases in maize. Accurately identifying diseases that affecting maize leaves is essential for guaranteeing a healthy maize harvest and is a considerable issue for farmers who lack specialized experience. The traditional method of identifying maize leaf diseases depends on physical leaf inspection and the knowledge of plant pathology expertise. However, there is a chance that the diseases may be misinterpreted, which would result in inefficient pesticide treatments. This not only hurts the ecosystem but also makes maize crops more vulnerable to damage. As they seem identical, the appearance of regions suffered with numerous illnesses can occasionally be challenging to distinguish with human vision. Therefore, it is essential to offer a realistic, automated system for identifying maize leaf disease. The creative use of artificial intelligence through machine learning is substantially facilitating the development of automated disease detection and categorization. Artificial intelligence is achieving remarkable advancements in bridging the gap between human and computer capacities. Even with little to no human involvement, the automated application of pesticides and fertiliser may be more effective. The benefits of intelligent agriculture will therefore be brought about. As a result, the treatment for corps disorders, which can be recognised from its images, will be accurate. Segmentation, masking, thresholding, clustering, edge detection, histogram analysis, and other image processing techniques have been primarily utilized to diagnose plant diseases [4, 5]. Using conventional image processing techniques to analyze a picture of a maize leaf normally yields misleading findings since the background of such images is frequently complex and irregular. Convolutional neural network (CNN) is a key machine learning (ML) method in computer vision. When compared to traditional machine learning-based classifiers, the innate filtering and automatic feature extraction capabilities of deep Convolutional Neural Networks are showing great promise and effectiveness in addressing image classification and segmentation challenges across various domains, ranging from medical applications [6, 7] to plant disease detection. CNN can memorize these filter properties, as opposed to hand-engineered filters utilized in early approaches, given enough time and effort. As a result, a well-built CNN model with effective image preprocessing may be able to identify the disease from a picture of a maize leaf.

This information served as our inspiration for categorizing numerous maize leaf diseases using a variety of state-of-the-art deep learning-based algorithms, and we chose the best model (ResNet18) to build the system in a website framework. This classification system was created with four classes in mind: three for maize leaf diseases (blight, common rust, and grey leaf spot), and one for healthy state. The pictures have been prepared for training using some basic image processing techniques, and models have been customized for quick operation and little storage. These classifiers have been designed, trained, validated, tested with tuning to superior performance. We also offer a comparative analysis of the findings based on accuracy, training time, model size, and other factors. After attaining positive results across all segments, the ResNet18 trained model has been incorporated into the website structure for usage in practise. For every image of maize leaf supplied to the web, the system can properly identify the disease class and estimate the probability that the model would be correctly diagnosed. To the best of our knowledge, no one has ever employed this comprehensive, web-based approach of processed and synthesized maize leaf categorization.

2 Literature Review

A number of significant studies have paved the way for the development of the categorization of maize leaf diseases. These ground-breaking studies have considerably advanced our knowledge of disease identification and categorization in relation to the production of maize. In this part, we highlight a few of the outstanding contributions that have helped to define the classification of maize leaf diseases.

Several studies have employed various machine learning techniques to classify maize leaf diseases, including Random Forest, Neural Network, and Naive Bayes. These studies typically involved four disease classes: healthy leaves, grey leaf spot, blight, and common rust. One such study achieved an average accuracy of 90.09% using the Histogram of Oriented Gradients (HOG) approach on a dataset of 3500 corn leaf images [8]. Another study by Md. Ashraful Haque et al. used Inception-v3 models to categorize images into four categories, including Healthy, Maydis Leaf Blight, Turcicum Leaf Blight, and Banded Leaf and Sheath Blight. Data augmentation techniques were applied to address class imbalance, resulting in a dataset of 13,971 images. The Inception-v3_GAP model achieved an impressive accuracy of 95.71% [9]. Hamish A. Craze et al. compared deep learning models trained on mixed disease field images with and without background subtraction. Their dataset included 2,332 images from field conditions, which were augmented to 18,656 images. The GLS_net_pv model achieved 94.0% accuracy on the PlantVillage Testing Dataset but had lower accuracy in identifying GLS disease [10].

Sumita Mishra et al. introduced a real-time approach for maize leaf disease identification using a deep learning model deployed on a Raspberry Pi with the Intel Movidius Neural Compute Stick. Their dataset had three classes, and the model achieved high accuracy, initially 98.40% with a GPU and later 88.66% after optimization [11]. Helong Yu et al. used K-Means Clustering combined with deep learning to identify grey spot, leaf spot, and rust. Their dataset contained 900 images, and the proposed CNN model achieved an impressive accuracy of 93.40% [12]. Pamungkas et al. employed pre-trained transfer learning models on a Kaggle dataset of 4,188 images related to maize diseases. The EfficientNetB0 and ResNet50 models reached accuracies of 94% and 93%, respectively, though some overfitting concerns were existent [13].

It is clear from the research reviewed above that plant diseases often have a regional focus because of differences in environmental conditions and geographic locations. To identify plant diseases more precisely, many researchers have proposed deep learning-based methods. Notably, deep learning models are frequently advised when access to large datasets is available. With a dataset of 4188 photos, our current study compares the findings of several customized models that treat three diseases in corn leaves. In the subsequent section, we have introduced an automated website that uses the best deep learning model among them for disease prediction.

3 Methodology

The primary steps of the proposed research involve pre-processing, training, and validation of several Convolutional Neural Network (CNN) models for the categorization of maize leaf diseases. The entire workflow is succinctly illustrated through the following flowchart, wherein each block signifies a distinct step within the process. These include the following: image acquisition, dataset, data preprocessing, augmentation, feature extraction, use of various CNN models via transfer learning, and classification.

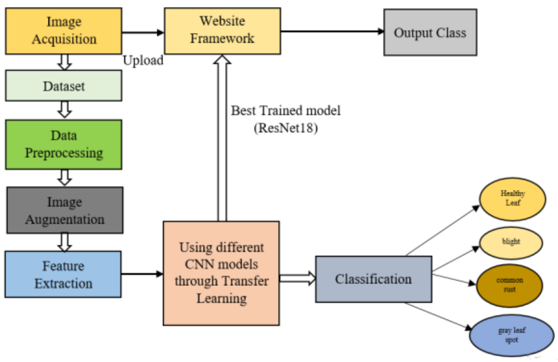


Fig.1. Overview of Proposed Method

The whole process we provide is shown in Figure 1. The initial stage of the process involves image acquisition from numerous sources. Hardware could be a part of this, such cameras or sensors. The dataset, which consists of a collection of photos representing the four classifications we want to predict, comes next. The models are trained using a wide range of images from this dataset in order to increase accuracy. Data preparation comes next in the process. This includes cleaning up the data once it has been acquired, fixing discrepancies, and resizing. This process seeks to assure a refined dataset to improve accuracy. We also used augmentation as it's a technique that artificially expands the quantity of our training data by introducing numerous modifications and adjustments to the original images. This procedure generates slightly modified new copies of the pictures, which reduces overfitting and improves the model's capacity to generalize to unknown data. Several transfer learning models are used in the next feature extraction process to isolate and keep only relevant and essential features. We then train and test the dataset using these models. On the other hand, we developed a website where trained ResNet18 model is provided for practical use. The website can estimate the disease class with probability of the correct classification when a raw picture is provided.

3.1 Dataset Description

The dataset used in this study was provided by Smaranjit Ghose [14] and was obtained via Kaggle. A variety of pictures are derived from this dataset. A total of 4188 RGB images from four distinct classes make up this dataset. These images have different pixel sizes. The main objective of this research is to categorise these four types of maize leaves autonomously using deep learning algorithms via a customised website. Figure 2 displays a few examples taken from the dataset.

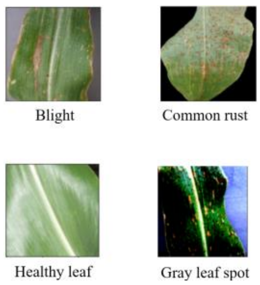


Fig.2. Types of Corn Leaf classes [14].

3.2 Data Preprocessing

The input data frequently contains noise, outliers, missing values, and other irregularities. To overcome these challenges, data preprocessing is used to reduce noise, fill in missing values, and coherently organize the data to improve accuracy. This stage covers three key processes: data cleansing, data transformation, and data reduction. It is essential to use pictures that are the same size when enabling network training. Therefore, image resizing becomes a crucial stage in this process. Images of various dimensions are scaled to fit the specifications of the model. During the resizing process, the RGB picture is separated into three distinct channels: R (red), G (green), and B (blue). Each channel is represented by a 2-dimensional matrix. Every channel is independently resized after that. The rescaled RGB picture is then created by combining the resized R, G, and B channels. In addition, the dataset is split into three parts for dataset management: 70% for training, 20% for validation, and 10% for testing.

3.3 Image Augmentation

It is crucial to use image augmentation due to the limited amount of training images available for a CNN network. This augmentation is crucial to simulate variations that may occur during image capture, such as different orientations and added noise. Our augmentation strategies include rotating the images by 90°, 180°, and 270° to account for various orientations. We also included Gaussian noise to simulate noise that could be present during picture acquisition. These augmentation methods provide robust performance in real-world contexts by assisting the network in adjusting to changes in orientation and noise. Additionally, image augmentation adds randomness and variability to the training data, which makes it harder for the model to overfit. It encourages the model to learn more robust and general features.

3.4 Feature Extraction using different DL models and Classification

We used a variety of transfer learning techniques built on Deep Learning (DL), which work by collecting input images and focusing on specific objects to distinguish between them. Contrary to other classification algorithms, Convolutional Neural Networks (CNNs) are notable for their decreased dependence on intensive preprocessing. Contrary to more straightforward methods that need manual filter crafting, CNNs can automatically learn out these filters or distinguishing characteristics with enough training. A list of the models that were applied in this research are given below:

VGG16: VGG16 analyses pictures with 224x224 pixels. It uses 3x3 filters in 13 convolutional layers, followed by ReLU activation [15]. Stride 2 and 2x2 window max pooling minimize feature map size. The architecture has three fully connected layers, ReLU activations (except the last), and a softmax output for class probabilities.

VGG19: The concepts of VGG16 are expanded upon in VGG19, which goes farther with 16 convolutional layers grouped with ReLU activations [15]. Using 3x3 filters, stride 1, and padding, it keeps the picture size at 224x224. It adds max-pooling after convolutions to reduce feature maps, just like VGG16. VGG19 has 3 fully connected layers, mostly flattened convolutions with ReLU and in the last layer a softmax layer is used for class probabilities.

AlexNet: AlexNet comprises 8 layers, including 3 fully connected and 5 convolutional layers [16]. Images are 227x227 RGB in size. Initial layers use various filter sizes. Map size is decreased via max-pooling with 3x3 filters and stride 2. The normalization of local responses helps in feature separation. The last layers are fully connected: 4096 neurons for the first two, 1000 for the final (matching ImageNet classes). ReLU activation is used, and a softmax generates class probabilities.

MobileNetV2: MobileNetV2 uses depthwise separable convolutions, linear bottlenecks, and inverted residuals for efficiency [17]. The core concept is Depthwise Separable Convolution, reducing computational load. Inverted residuals expand, convolve, and reduce channels. It employs ReLU6 activation for stability and down-sampling for efficiency. Customized versions can include average pooling, Dropout, and Fully connected Dense layers.

SqueezeNet: SqueezeNet relies on "Fire Modules," which have two key components: the "squeeze layer" uses 1x1 convolutional filters to decrease the input's channel depth, the "expand layer" combines 1x1 and 3x3 convolutional filters to efficiently increase channel depth [18]. These Fire Modules are stacked to build the network. Spatial dimensions are reduced using max-pooling and strided convolutions. Instead of large fully connected layers, SqueezeNet employs global average pooling. A single fully connected layer is added for final class scores, and ReLU activation functions enhance feature learning. This design minimizes parameters and computations while maintaining accuracy.

ResNet18: ResNet-18 is a well-known convolutional neural network architecture valued for its effectiveness in tasks like image classification and feature extraction [19]. At its core are "residual blocks" devised to combat the vanishing gradient issue in deep networks. Each residual block comprises two main paths: the "shortcut" or "identity" path and the "main" path. The main path typically includes a sequence of convolutional layers using 3x3 kernels, followed by batch normalization and ReLU activation functions. Meanwhile, the shortcut path directly passes the input to the block's output. The breakthrough idea of ResNet is its "skip connections" or "identity mappings," which facilitate gradient flow during training, enabling the training of very deep networks. By adding the shortcut's output to the main path's output, ResNet effectively learns the "residual" or the difference between the desired and predicted outputs.

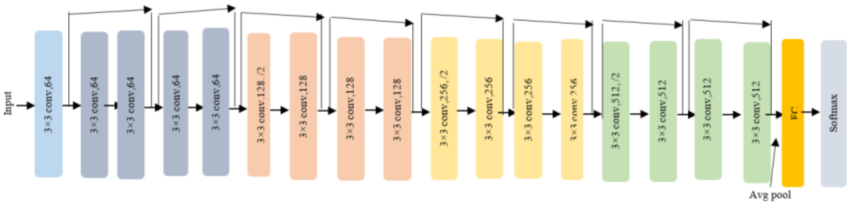


Fig.3. Customized ResNet18 architecture for corn leaf disease classification.

ResNet-18 comprises multiple such residual blocks, with the standard configuration using four blocks, each having several convolutional layers. To reduce spatial dimensions in deeper layers, ResNet employs strided convolutions or max-pooling. Instead of conventional fully connected layers at the end of the network, ResNet-18 opts for "global average pooling" (GAP). GAP computes the average of each feature map across all spatial locations, yielding a fixed-size feature vector for classification. Finally, a fully connected layer with softmax activation produces the ultimate class scores for classification.

3.5 Website Development for practical application

As part of the website's development, the trained model ResNet18, which can identify diseases affecting maize leaves, was seamlessly integrated. This integration makes it possible to concurrently classify the four classes of maize leaf with probability of accurate identification for this model.

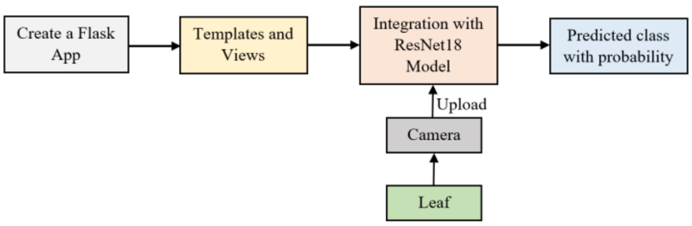


Fig.4. Flow diagram of website development for classification.

To make it easier to integrate the model with the website, the Flask framework is used. Flask, which is renowned for its effectiveness and adaptability, provides useful tools and features that simplify the development of web applications in Python. Figure 4 depicts the overall flow diagram for our website based categorization of maize leaf diseases.

4 Result and Discussion

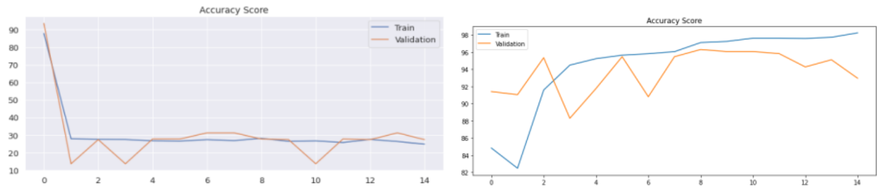
For the purpose of classifying maize leaf diseases, we evaluated a wide range of transfer learning models in this work. Our primary goal was to evaluate how well different models handled accurately identifying the existence of diseases in maize leaves. The results of the research offer crucial details about these models' capabilities and demonstrate how they may be applied in actual agricultural situations. Python and PyTorch are used to create the classification system for maize leaf disease and train the models. The main platforms for model training and evaluation are Google Colaboratory with 12.7 GB RAM and 12 GB NVIDIA Tesla K80 GPU and Kaggle with 16 GB RAM and 13 GB NVIDIA Tesla P100 GPU.

Table 1. Performance comparison with respect to evaluation metrics

Model	Accuracy (%)	Recall (%)	Precision (%)	F1 Score (%)	Training Time (Sec.)	Model Size (MB)
VGG16	95.50	95	95	95	812.0	553.45
VGG19	95.02	95	95	95	934.0	574.69
AlexNet	95.50	95	96	95	599.2	244.42
MobileNetV2	93.36	93	94	93	540.9	14.27
SqueezeNet	95.26	95	95	95	544.9	**5.02**
ResNet18	**96.45**	**96**	**96**	**96**	**540.4**	44.79

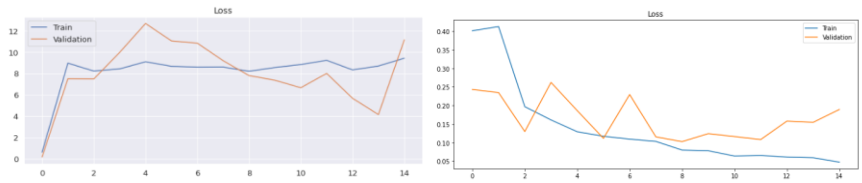
The outcomes decide how effective such models are. In this work of identifying maize leaf diseases, evaluation criteria such as confusion matrix, accuracy, precision, recall, f1 score, training duration, and model size have been employed. The accuracy, training duration, model size, and other evaluation results for all models are displayed in Table 1. With a remarkable accuracy of 96.45%, the ResNet18 model lead the field in the categorization of diseases. The accuracy of the VGG16 and AlexNet models not far behind, was 95.50% respectively. SqueezeNet and VGG19 se-cured accuracies of 95.26% and 95.02%, respectively, while MobileNetV2 attained a slightly lower accuracy of 93.36%.

It's intriguing to note that model architecture's complexity and performance seem to be related. ResNet18, which had a model size of 44.79 MB and a shorter training time of 540.4 seconds, demonstrated outstanding accuracy, showing the potential benefits of a reduced model size. Similar results were obtained using AlexNet, which has a model size of 244.42 MB and a training time of 599.2 seconds. AlexNet likewise demonstrated the ability to successfully capture complex disease patterns. ResNet18 and MobileNetV2 models' training and validation accuracy and loss are shown in Figures 5 and 6, respectively. On the other side, models of smaller size, such MobileNetV2's 14.27 MB model size and 540.9 second training time, had less accuracy. The intrinsic trade-off between model complexity and generalization capacity may be responsible for this. Smaller models may have trouble capturing complex disease details, but they tend to generalize more well across diverse datasets. SqueezeNet model, on the other hand, has superior accuracy of 95.26% and has a much smaller model size (5.02 MB) and shorter training time (544.9 Seconds). The confusion matrix for ResNet18 and MobileNetV2 is shown in Figure 7 correspondingly. ResNet18 therefore displays the overall best outcome among all of the cutting-edge techniques used in this study.



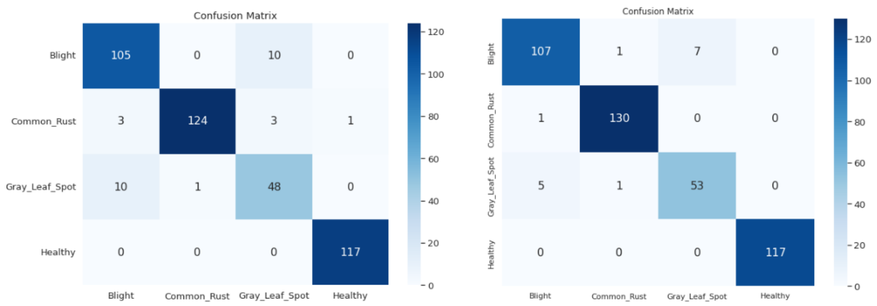
(a) MobileNetV2 (Poor Result) (b) ResNet18 (Best Result)

Fig.5. Training and validation accuracy graph of transfer learning models.



(a) MobileNetV2 (Poor Result) (b) ResNet18 (Best Result)

Fig.6. Training and validation loss graph of transfer learning models.



(a) MobileNetV2 (Poor Result) (b) ResNet18 (Best Result)

Fig.7. Confusion Matrices of transfer learning models.

Table 2. Comparative analysis of classification results with recent related studies.

Study	Images in Dataset	Method	Accuracy
Ubaidillah et al. [6]	3500	Random Forest + Neural Network + Naïve Bayes	90.09%
Md. Ashraful Haque et al. [7]	13971	Inceptionv3_GAP	95.71%
Hamish A. Craze et al. [8]	18,656	GLS_net_pv	94.0%
Sumita Mishra et al. [9]	4382	Optimized CNN deployed on NCS	88.66%
Helong Yu et al. [10]	900	K-Means Clustering with CNN	93.40%
Wisnu Gilang Pamungkas et al. [11]	4188	EfficientNetB0	94%
This study	4188	ResNet18	**96.45%**

The ResNet18 model's outstanding accuracy indicates its capability as a reliable tool for automated maize disease diagnosis. However, it's important to note that a model's accuracy alone might not be the sole determinant of its real-world usability. Aspects including deployment speed, requirements for resources, and adaptation to changing agricultural circumstances must also be considered.

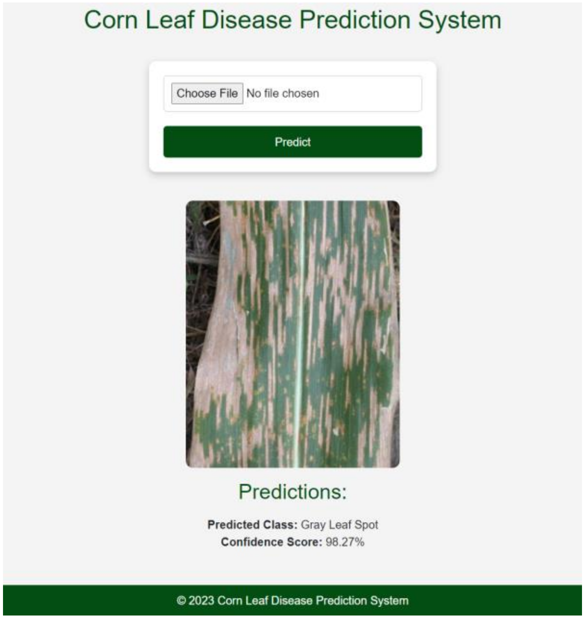


Fig.8. Website preview of the corn leaf disease.

According to our research, selecting a model must be done with great care. Depending on the specific requirements of an application, a balance between model accuracy and complexity can be struck. Models like ResNet18 and SqueezeNet could offer the best balance between performance and efficiency for situations with limited resources. The performance of several models from the corresponding papers are compared in Table 2. We discovered that all of the transfer learning models in our study perform quite well since the dataset after augmentation contains a wide variety of pictures and the models are customized. As a result, we did not concentrate on developing a new model as all existing models already had accuracy in the saturated level. Instead, we concentrated on creating a complete system featuring a lightweight yet high-performing model. Figure 8 displays the website's preview. The system's primary objective is the accurate and efficient identification of maize leaf diseases using an intuitive user interface. Users may quickly and reliably detect these diseases with our solution, which is designed to offer a simple and straightforward experience.

5 Conclusion

In this work, we focused on categorizing distinct disease in four different classes of maize leaves using a variety of transfer learning models. Our strategy includes utilizing a dataset with a wide range of maize leaves revealing various diseases. Through transfer learning, these leaves were preprocessed, enhanced, and used in combination with various conventional DL approaches, including VGG19, VGG16, SqueezeNet, ResNet18, MobileNetV2, and AlexNet. According to our research, SqueezeNet and ResNet18 performed better than the other approaches in correctly identifying maize leaf diseases. ResNet18, nevertheless, may have demonstrated the greatest performance across all matrices. Notably, we found that accuracy may be increased even with models with fewer layers by carefully changing training parameters, such as the learning rate, number of epochs, and optimizer selection. To boost efficiency and storage appropriateness for quicker operations, each model underwent customization. The website we designed allows users to accurately categorize uploaded photos of maize leaves using a trained ResNet18 model. This innovative solution not only identifies the disease class for each image but also provides the probability score for accurate classification. This thorough method makes disease identification simple, enabling farmers to safeguard their crops effectively. In the future, we intend to broaden our study by incorporating more disease types and algorithms. This expansion aims to make disease detection even more comprehensive, user-friendly, and expedient. Investigating ensemble approaches, which incorporate the positive features of multiple models, may produce even more reliable results. Additionally, investigating strategies to overcome the difficulties provided by unbalanced datasets and varying illumination conditions may improve the practical applicability of these models. In keeping with our core goal, we remain committed to design an entire system that includes a lightweight, high-performance model that can quickly, easily, and precisely detect maize leaf diseases.

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