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An intelligent leaf disease prediction for corn and maize using Convolutional Neural Network

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Abstract:

About 40% of Indians are directly engaged in agriculture and 20% are indirectly engaged in agricultural jobs. The most widely grown crop worldwide is corn which is used in numerous agricultural products, including those that can be used to make biofuels, as well as in the food chain. In India, a large number of small-scale farmers rely on farming for both a living and for meeting their fundamental necessities. Conversely, corn crops are susceptible to illnesses that hamper crop yield and farmer income. Temperature fluctuations and unfavorable weather patterns cause the disease to spread. With the development of digital technology, the use of technology in farming and agricultural operations has widened. Farmers can use voluminous volumes of data regarding crop and soil conditions, climate change, and other environmental factors to guide their decisions about how to handle plants and animals through the use of machine-learning methods in agriculture. A modified deep transfer learning is implemented in this work, which classifies three major corn diseases and identifies healthy images among them. In this work, the most prevalent diseases were taken into account, including blight, gray leaf spot, and common rust. For forecasting the classes, Resnet-18, a type of convolutional neural network was deployed. The corn leaf image is provided as input and the transfer learning technique was established on Resnet-18 and the data was split extensively for multiple scenarios. It is classified into four classes and obtained a mean accuracy of 96% than the existing schemes.

Keywords- ResNet-18, Convolutional Neural Network, Leaf diseases, Deep Learning, Corn.

1. Introduction

Leaf diseases represent the primary causes of crop failure, resulting in an approximate annual global output reduction of US$2000 billion [1,2]. Plant health can be compromised by fungal, viral, or bacterial infections, leading to alterations in color, shape, or margins, and impacting leaves, fruits, or branches. Therefore, it is crucial to look at potential quick detection, control, and treatment solutions. The conventional method of the naked eye examination is the primary defense in disease identification, however, it is ineffective [3,4,5]. Farmers may also use the incorrect chemical or treatment procedure [6]. This sort of infection typically requires analysis and discovery by a plant pathologist, which can be expensive, slow to act, or all of the above inaccessible [7, 8]. A crop that is widely grown in big amounts is a maze, which is also known as maize. It acts as the basic raw component for a various of other products, such as cooking oil, animal feed, flour, alcohol, starch, and biofuel, apart from being consumed directly as a food source. Alongside rice and wheat, corn stands out as one of the most crucial crops due to its substantial genetic variation and capacity for production, thriving across diverse environmental conditions [9]. In 2020, there were 1.15 billion tonnes of corn produced worldwide [10]. It is inherently vulnerable to a wide range of ailments that can affect the plant's leaves, trunk, and fruit at any stage of development. This directly affects corn harvest yield, which results in significant financial loss. Food shortages, famine, and possibly hunger may occur from the global production of essential crops like corn being reduced [11]. The most deadly of these ailments are those that affect the growth of maize leaves. In this work, Cercospora Leaf spot, Northern leaf blight and common rust are three general leaf disease used [12].

The Cercospora leaf spot is caused by the fungi Cercospora zeina, and Cercospora zeae-maydis which alters the color and appearance of the leaves. These fungus live on the surface of the soil and produce necrotic lesions that range in color from black to grey and they demand a warm, moist environment. The administration of an appropriate fertilizer is a common treatment, but it has to be used before grain formation [13,14]. Another fungus illness brought on by the Exserohilum turcicum fungus is Northern Leaf Blight. Crops that are in the process of growing and reproducing could suffer substantial losses if they strike during these times. Also, certain meteorological circumstances make it worse and deteriorate the growth of crops. The disease manifests itself on the leaves as angular, rectangular-shaped dark brown dots. The appropriate chemical agent is used to treat the disease [15,16]. On the upper and lower surfaces of maize leaves, common rust manifests as dark, reddish-brown blisters and is brought on by the fungus Puccinia sorghi. Acceptable chemicals are used to treat it [17–19].

Modern technology has led to several breakthroughs in agriculture. Specifically, ML and DL applications are affected by plant pictures. Convolutional Neural Networks

(CNNs) are a type of DL network that utilise an architecture comprising rectified linear unit, convolutional, and pooling layers that feed into a fully associated layer. CNNs aim to detect image characteristics and associations. The various characteristics that the prior layers have uncovered are included in this layer. Despite multiple modifications that could affect the input images, CNNs are excellent at recognizing features [20]. When building systems based on CNNs, researchers have the option of starting from scratch or applying transfer learning. The process of reusing models and applying new approaches to innovative applications is called transfer learning. Following this technique, Deep transfer learning transforms contemporary models with partial or complete retraining in a way that suits the new application. It has the benefit of using earlier layers to identify generic properties (such as colors and borders) and tailoring subsequent levels for particular applications.

On the farmer's side, a CNN model is developed that can feed images directly from farmers' laptop computers. The model then performs disease detection and applies strategies for resizing and normalizing each dataset. Although data augmentation procedures are only used on the trained set to enrich the data with the intent that the model may generate more accurate findings. The model then displays the disease category as well as the confidence percentage and classification time it took to process the image. Farmers with minimal resources can now take photos of the infected plant leaves using a web app. On the user side, the web application runs on top of the CNN model. The application also shows the classification time required to process the image and the confidence percentage. In particular, a system is developed which is working locally on the PC of the user. We used an open-source dataset from Kaggle that included 4188 images of the three most prevalent diseases (common rust, gray leaf spot, and blight) as well as a healthy type. Major contributions of the proposed work are,

- Implementation of a web-based method for real-time identification of leaf diseases using transfer learning techniques.
- A technologically modified CNN model is implemented in which the farmers can directly feed images from their system.

In order to provide a disease detection tool that is both successful and easy to use, the Corn Leaf Disease Detection application with Gradio requires a number of critical user needs. The proposed structure has the following important features:

- **Easy-to-use interface:** Even for users who are unfamiliar with ML techniques or agricultural terminology, the Gradio interface for the disease detection tool is simple to use.
- **Quick and accurate results:** Users should be able to quickly and accurately obtain results for the disease detection tool. The tool should be able to process images quickly and provide accurate disease classifications within seconds.
- **Accurate disease classification:** The disease detection tool should be able to accurately classify corn leaf diseases, even when there are multiple diseases present in the same leaf or when the disease is in its early stages.
- **Clear and concise results:** The disease detection tool should provide clear and concise results that are easy for users to interpret. This may include visualizations or textual descriptions of the disease classification.
- **Reliable and secure:** Users should be able to trust that the disease detection tool is reliable and secure, with no risk of data breaches or other security issues.

In particular, the Corn Leaf Disease Detection method with Gradio is focused on creating a user-friendly and effective disease detection tool that is accessible to an extensive range of users

The rest of this study is outlined as follows. The background, current situation, and recent developments for leaf disease detection are included in Section 2 . The requirements for deploying the proposed approach into practice are then briefly outlined. The proposed approach for addressing the challenge of detecting maize leaf disease is discussed in Section 4 along with some discussions. The findings of the simulation and testing are exhibited in Section 5, and the conclusion is specified in Section 6.

2. Related works

The contemporary schemes that are related to corn disease detection and the gaps found in the existing models are discussed in this section.

Rajeev et al. [21] used AlexNet a type of CNN model that has 5 convolution layers and 3 max pooling layers. In this technique, CNN was able to extract features directly by processing the raw images directly. However, it experienced lower accuracy for a lower number of epochs.

Ali et al. [22] used CNN and image processing techniques for classifying the potato images into 5 classes namely Black Leg, Black Scurf, Pink Rot, Healthy, and Common Scab. This work utilized around 5000 images and achieved an accuracy of 99-100% in some of the classes. But, this technique failed to detect plant images with multiple diseases.

Monzurul et al. [23] used Multi-class support vector machines, imaging, and computer vision based on phenotyping were used to classify the potato images. This work demonstrated an accuracy of 95% on a dataset of around 300 images and opened the door for automated plant disease detection on a larger scale. But this technique used a very small dataset and the accuracy obtained is not precise. It was not able to perform with imbalanced image classes and also the noisy data provided uncertain results.

To start transfer learning for the categorization of corn illnesses, Wei et al. [24] introduced VGGNet, a form of CNN, together with the Adam optimizer. The evaluation score for this model is exceptionally high, with a 94.64% recognition rate. In contrast, this method was unable to identify plant images with numerous diseases.

Javed et al. [25] proposed a deep learning (DL) model with multiple layers to detect illnesses in potato leaves. At first, the YOLOv5 image segmentation algorithm was used to separate the leaves from photos of potato plants. To differentiate between matured blight and premature blight on potato leaves, a separate DL method was created at the second level.Our technique was less parameter-intensive and easier to implement than state-of-the-art approaches; it also considered for the effect of environmental variables on potato leaf diseases.

Pan et al. [26] increased their collection of 985 photos of healthy and diseased maize leaves to 31,005 images using data augmentation techniques such as image scaling, image transformation, image segregation, and resizing an image. The pytorch and kerras frameworks were used to implement numerous tested CNN models. With a 99.94% accuracy rate, the proposed methodology produced excellent results and an informative diagnosis of NCLB. Adversarial network-based data augmentation approaches can also improve the effectiveness of visual feature detection during the training of the DCNN models.

Divyanth et al. [27] developed a CNN model In order to identify diseases in maize that combines depth with conventional artificial and feed-forward neural network methods. They introduced a new method for detecting and evaluating maize illnesses using a two-stage semantic segmentation procedure. During each step, semantic segmentation models were trained using various network architectures, including SegNet, DeepLabV3+, and UNet. The recognition rate and speed of this method are very high. It eliminates interference from the outside environment, quickly and accurately detects and identifies information on maize disease, and significantly increases detection accuracy. This method should take into account the various traits of diseases at various phases of disease development because incorrect decisions could have an impact on the recognition rate.

Malusi et al. [28] used Neuroph to train a convolutional neural network (CNN) in order to classify and identify maize leaf diseases.In order to build a more robust CNN, the convolution and pooling feature extractions were integrated into the Neuroph library, which served as an IDE. However, this approach has difficult outputs of greyscale images because its resolution setting is limited to 10*20*3 (height*width*RGB).

Farah et al. [29] suggested using Partial Least Squares (PLS) regression to choose characteristics from a deep feature set obtained in an automated crop disease recognition system.Compared to the initial feature vectors, it used a fusion procedure that consumed longer to execute. The final vector also has a selection that failed to take into account some of the key attributes, which results in a very low accuracy.

Manavalan [30] examined around 109 articles that reported on early disease detection to upsurge production. The study's findings demonstrate that autonomous systems for diagnosing and classifying grain plant diseases are quite an infant stage. However, this research had trouble differentiating between diseases with related characteristics.

3 Prerequisites

The system presumes that input images are of high quality and depict corn leaves. It also postulates that input images are correctly labeled according to their corresponding disease category. The system is constrained by the availability of labeled corn leaf images to train the ResNet-18 model.

3.1. System Requirements

The hardware requirements for the Corn Leaf Disease Detection project with Gradio would depend on the scale of the project and the size of the dataset. The application runs on a Central Processing Unit (CPU), but training and inference times may be slower compared to running on a Global Processing Unit (GPU). A GPU with CUDA support can significantly speed up training and inference times, especially for large datasets. The capacity of Random Access Memory (RAM) required depends on the dataset size, but at least 8GB of RAM is recommended. Storage requirements are determined by the dataset size and the model checkpoints number saved during training.

Table 1: The approach for detecting corn leaf disease requires specific software

Name of the software	**Descriptions**
Python	Python 3.7
PyTorch	Deep learning library
Gradio	Web interface
NumPy	Numerical computing
Matplotlib	Data visualization
OpenCV	Image processing
Pandas	Data manipulation
Flask	Backend server for the Gradio web interface
TorchVision	Image processing
CUDA Toolkit	Optimal performance

A very high network connection is required to install and download the necessary libraries and tools. Overall, the Corn Leaf Disease Detection application with Gradio executes on a standard computer with a CPU and at least 8GB of RAM. However, for optimal performance, a GPU with CUDA support and more RAM would be recommended, especially for larger datasets. Table 1 demonstrates the software requirements for the Corn Leaf Disease Detection application with Gradio. The software requirements for the Corn Leaf Disease Detection project with Gradio are mainly Python libraries and tools, along with Flask for the web interface.

4. Proposed work

A detailed explanation of CNN architecture, the proposed system, and the pre-trained model which is used is discussed in this section.

Residual Neural Network (ResNet), a CNN architecture, is utilized to create networks that outperform shallower networks by having up to hundreds of convolutional layers. This study makes use of ResNet-18, one of the variations that offer the benefit of being able to train on over a million photos in the ImageNet database. It consists of 18 layers of depth and is constructed with 72 layers. It classifies images into 1000 dissimilar object classifications, making it incredibly effective and useful in image classification. This enables a larger amount of CNN layers so that the classification is performed efficiently. However, having multiple deep layers leads to a vanishing gradient problem. ResNet's main goal is to employ jumping connections, frequently referred to by the terms shortcut connections or identify connections and the connections utilize the activation of previous layers. These hop from one layer to another creating a shortcut linkage between them. These identity mappings initially skip connections, using previous layer activations as a result. The skipping procedure compresses the network and henceforth learns earlier. After compression is completed, layer expansion occurs allowing the remaining parts of the network to train and explore feature space simultaneously. The network's input size is 224*224*3, which has been predetermined. The network's intricate layered architecture essentially qualifies it as a Directed Acyclic Graph (DAG) network. Furthermore, it receives input from numerous layers and outputs to numerous layers.

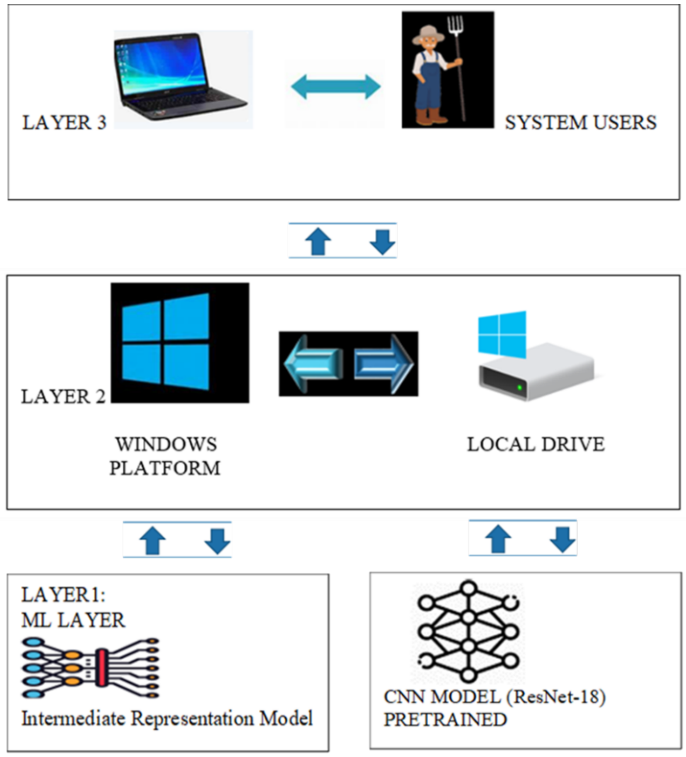

Figure 1: System architecture

The proposed system architecture for the user-side laptop implementation of the maize leaf disease detector is shown in Figure 1. Layer 1 defines the Intermediate Representation (IR) model that runs on the device and undergoes training using the dataset, in addition to the deep learning model employed by the system (i.e., ResNet-18). The user interface based on Gradio that offers system users an interactive user interface is depicted in Layer 2 of the diagram. A detailed explanation of the architecture is given below,

- **User Interface:** Users can submit images of maize leaves to the Gradio interface's web-based user interface to receive predictions for the disease label associated with those images.
- **Application logic:** The application logic includes the machine learning model that was accomplished to detect several forms of corn leaf diseases. This model is loaded into memory when the application starts up and is used to generate predictions for new images.
- **Gradio library:** The Gradio library provides the backend for the web-based user interface. It handles tasks such as uploading images, displaying predictions, and managing user interactions.
- **Deep learning libraries:** Deep learning libraries such as PyTorch and Torchvision are used to construct and train the ML model that controls the

application.

- **Deployment platform:** The application is deployed on a local machine
- **Data sources:** To train the ML model, the application incorporates a dataset of labeled images of maize leaves. The application often retrieves this dataset when training through a database or file system.

Overall, the system architecture of the Corn Leaf Disease Detection application with Gradio is a client-server architecture, where the Gradio interface acts as the client, and the application logic and deep learning libraries run on the server side. The deployment platform provides the necessary resources to run the application and manage user interactions.

The ResNet-18 model was used for categorizing diseases, followed by the proposed CNN that is based on data augmentation. The transfer learning process commences when data augmentation enhances the data, which in turn improves the generalization and accuracy of the model. Consequently, the ResNet-18 model is used for training which in turn accelerates the training process of CNN and uses test data feedback network training results. Using a pre-trained model, one can then adapt it to a new application by changing the output type and class count, for instance. Initial layers in this approach identify common low-level features like colors, edges, and blobs before subsequently learning the precise feature the customer needs. This is preferable to establishing random beginning weights since it speeds up learning, which is used in the current systems. Additionally, it facilitates learning from fewer images. Figure 2 depicts the process flow of the proposed approach.

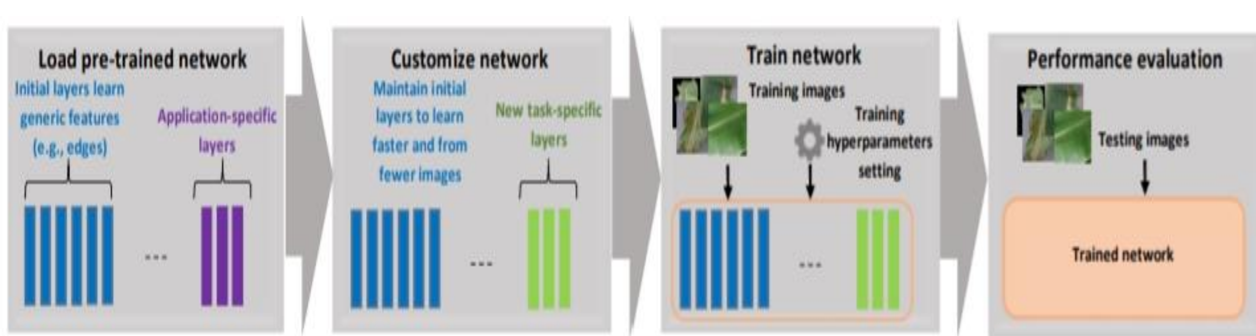

Figure 2: The process flow of the proposed disease detection framework

4.1 Distinctive features of the proposed identification technique

Some of the main characteristics of the proposed Corn Leaf Disease Detection application are listed below:

- **DL model:** The application uses a DL model based on the ResNet-18 architecture to find maize leaves diseases. An extensive dataset of more than 14,000 images of maize leaves was used to train the model, which contributes to its excellent accuracy in disease identification.

- **Gradio interface:** The project uses Gradio to provide a user-friendly and interactive interface for disease detection. The Gradio interface allows users to upload images of corn leaves, adjust the threshold for disease detection, and get accurate predictions for the category of disease existing in the leaves.

- **Multiple image upload:** The Gradio interface supports multiple image uploads, allowing users to upload and process multiple images of corn leaves simultaneously. This feature can help increase the efficiency of disease detection for large-scale agricultural operations.

- **Real-time prediction:** The Gradio interface provides a real-time prediction of disease presence in corn leaves as users adjust the threshold for disease detection. This feature allows users to see how the model responds to different thresholds and gain a better understanding of how the model works.

- **Cross-platform:** The Gradio interface is cross-platform, which means that it can be accessed from any device with a web browser. This feature allows users to access the disease-detection interface from a wide range of devices, including smartphones and tablets.

4.2 Non-functional Requirements

The system has an extreme accuracy rate in distinguishing corn leaf diseases in addition, it classifies corn leaf images in real-time or near-real-time, with minimal delay. The system has a user-friendly interface that allows users to easily upload images and view the classification results. The system is scalable, allowing for additional disease categories to be added in the future.

- **Data Loading and Pre-processing:** It involves loading the images and applying some pre-processing steps such as resizing, normalization, and data augmentation. The time complexity of loading and pre-processing is determined by the integral value of images and the size of each image. For n photos, the time complexity is $O(n)$because each image is processed once, assuming that each image has an average size of 256*256 pixels. The spatial complexity is proportional to the picture size and the number of images. The space complexity is $O(n * s)$where s is the size of each image, assuming that the images are stored in memory. The background pre-processing procedure is shown in Figure 3.

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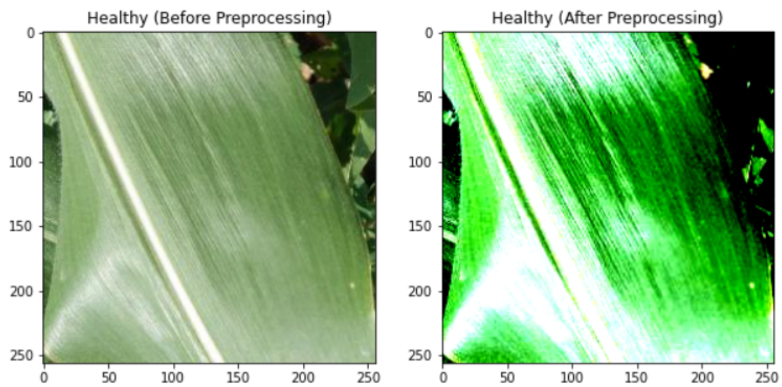


Figure 3: Process of data preprocessing

5. Results and Discussions

This section discusses the evaluation matrix and performance metrics used in this work. Detailed requirement analysis for both functional and non-functional is performed.

Based on the RAM capacity that is currently available, the starting batch size was set at 32 epochs. For the purpose of training the network, Stochastic Gradient Descent (SGD) was utilised, with a learning rate of 0.003. The dataset was partitioned into training, validation, and testing sets in order to accomplish data separation. Allocating 70% for training, 20% for validation, and 10% for testing was achieved using the split folder library. Data augmentation techniques were exclusively applied to the training set to enhance the dataset and improve the model's accuracy, while normalisation and resizing approaches were applied to all datasets.The following equations demonstrate some of the metrics that were used,

- $Accuracy = TP + \frac{TN}{TP} + TN + FP + FN$ (1)

- $Precison = \frac{TP}{TP+FP}$ (2)

- $Recall = \frac{TP}{TP+FN}$ (3)

- $F1 = 2 * \frac{precison*recall}{precion+recall}$ (4)

The True Positive (TP) symbol in equations (1-4) denotes a correctly classified leaf image among disease states. A False Negative (FN) occurs when a leaf image is incorrectly classified as healthy when actually it belongs to a disease category. A False Positive (FP) indicates that a healthy leaf image was mistakenly identified as an infection. Additionally, TN stands for "True Negative," which is capable of correctly identifying a healthy leaf in an image. Out of all the positive images, the true positive rate (TPR) measures the extent to which the model can classify a leaf image as belonging to the proper disease class. Sensitivity is another name for TPR. A high sensitivity level may lead to a large number of false positives (FP), but it also means that leaf images are being recognised as disease representations quickly. Precision measure is defined as the percentage of false positives relative to the total number of positives. Divide the total number of test images by the sum of TP and TN to calculate the accuracy. The F1 score is considered as an easier method to evaluate the model's performance in addressing class imblances, especially when dealing with different categories that have uneven image amounts.

- **PyTorch:** DL model for disease detection in maize leaves is implemented by PyTorch, an open-source ML package.

- **NumPy:** NumPy is a Python library for scientific computing that is used for numerical operations on corn leaf images.

- **Gradio:** Gradio is a Python library for building and sharing custom machine-learning interfaces. It is used to create a user-friendly interface for disease detection in the Corn Leaf Disease Detection project.

- **Pillow:** Pillow is a Python library for handling and processing image data. Whenever images of maize leaves are fed into the DL model, it is used to load and pre-process the images.

- **Matplotlib:** Matplotlib is a Python library for creating visualizations. It is used to visualize the corn leaf images and their predicted disease labels.

- **Pandas:** Pandas is a Python library for data manipulation and analysis. It is used to organize and manipulate the corn leaf image data.

- **Flask:** Flask is used to create a server for hosting the Gradio interface.It is python webframework

To guarantee the efficacy and precision of the disease detection model, the Corn Leaf Disease Detection application using Gradio includes domain-specific criteria. Some of the most important domain criteria for this approach are as follows:

- **Image quality:** The accuracy of the disease detection model depends on the quality of the input images. To ensure accurate results, the input images should be high-resolution and clear, with minimal noise and distortion.
- **Representative dataset:** When it comes to disease identification, the quality of the dataset means an excellent value. The training dataset should contain examples of all the many kinds of diseases that might harm maize crops so that the machine can identify them correctly in the leaves.
- The open source dataset is available on Kaggle i.e. the corn and maize leaf disease dataset which was primarily derived from a bigger dataset namely the plant village dataset is used. It comprises 4188 images divided into 4 classes given in Table 2.

Table 2: Classification of images with their count

Name of the disease	**Image count**
Blight	1146 images
Common rust	1307 images
Gray leaf spot	574 images
Healthy	1157 images

The images have been converted into jpeg format and have 256256-pixel sizes. There is just one leaf image in each file and Figure 4 following displays samples of various diseases.

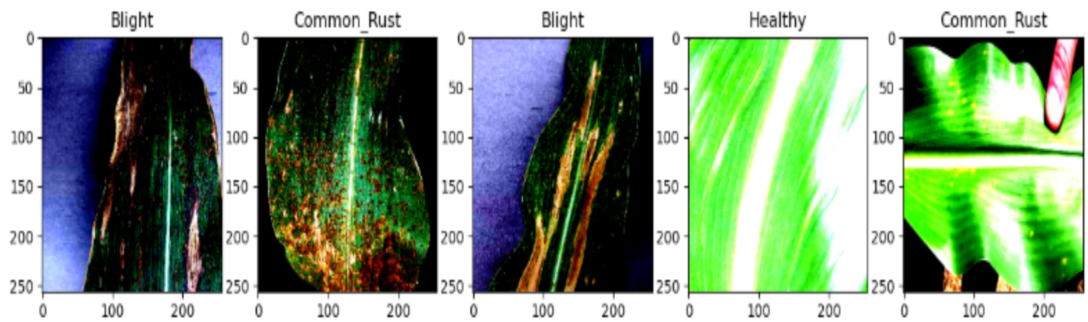


Figure 4: Sample images illustrating various disease

The disease detection model must be able to accurately classify corn leaf diseases into different categories. To do this, the model must be trained on a taxonomy of corn leaf diseases that is accurate and up-to-date. The development and refinement of the disease detection model may require input from experts in the field of agriculture and plant pathology. Experts can provide insight into the most common and dangerous corn leaf diseases and help identify the key features that should be used for detection. As new corn leaf diseases are discovered and identified, the disease detection model must be updated to ensure that it can accurately detect these new diseases. Real-time updates to the model can help ensure that it remains effective and relevant over time. Overall, the Corn Leaf Disease Detection project with Gradio has domain-specific requirements that are important for ensuring accurate and effective disease detection in corn crops.

Various DL models could produce different classification results, and need a variety of training and validation timeframes, otherwise favor some classes over others. Additionally, while some models might be able to generalize to new data, others might not, depending on the training set. Moreover, the performance review is the selection of the images for each subset is random (e.g., training). The experiment should be repeated until positive findings are obtained, although this will not accurately reflect the performance. ML models might also be prone to overfitting and underfitting. Resizing and Normalizing methods were applied to all of the datasets but data augmentation procedures only pertained to the train set to enrich the data so that the model possibly will yield more accurate results. The testing accuracy of the model which we were able to achieve was around 96% after running the experiment 30 times.

The proposed application's categorizing report is illustrated in Figure 5 below. Here, 0 denotes the Blight class, 1 denotes common rust, 2 denotes gray leaf spot, and 3 denotes the Healthy class.

```
In [19]: print(classification_report(test.targets, all_preds))
                  precision    recall  f1-score   support

               0       0.95      0.90      0.92       115
               1       0.98      0.99      0.98       131
               2       0.84      0.92      0.88        59
               3       1.00      1.00      1.00       117

        accuracy                           0.96       422
       macro avg       0.94      0.95      0.95       422
    weighted avg       0.96      0.96      0.96       422
```

Figure 5: Precision report

From the observations, it is proved the proposed application achieved a 100% score in a healthy class for all the 3 parameters. The recall, accuracy and F1-score for the common rust class were all around 98%, 99%, and 98%, respectively. The class was able to acquire a 95% precision score, 90% recall score, and an 92% F1 score of blight. An 84% accuracy, 92% recall, and an 88% F1 score of gray leaf spot is achieved. Further deep diving into the results Confusion matrix is plotted for the model which is given in Figure 6. Figure 5 displays the accuracy, train, and validation losses that were plotted, and Table 3 lists the findings.

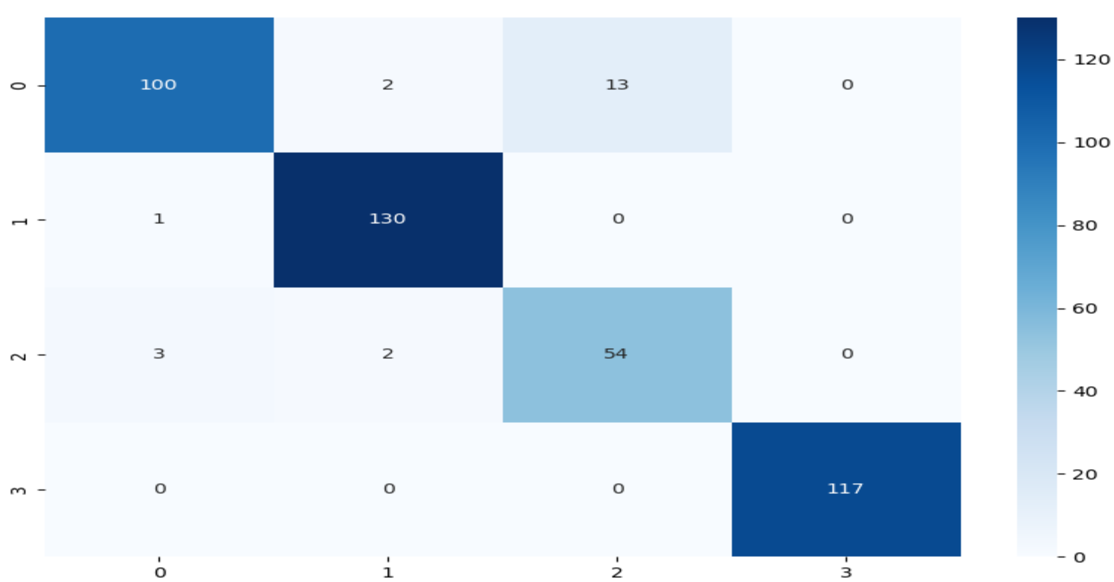


Figure 6: Confusion matrix

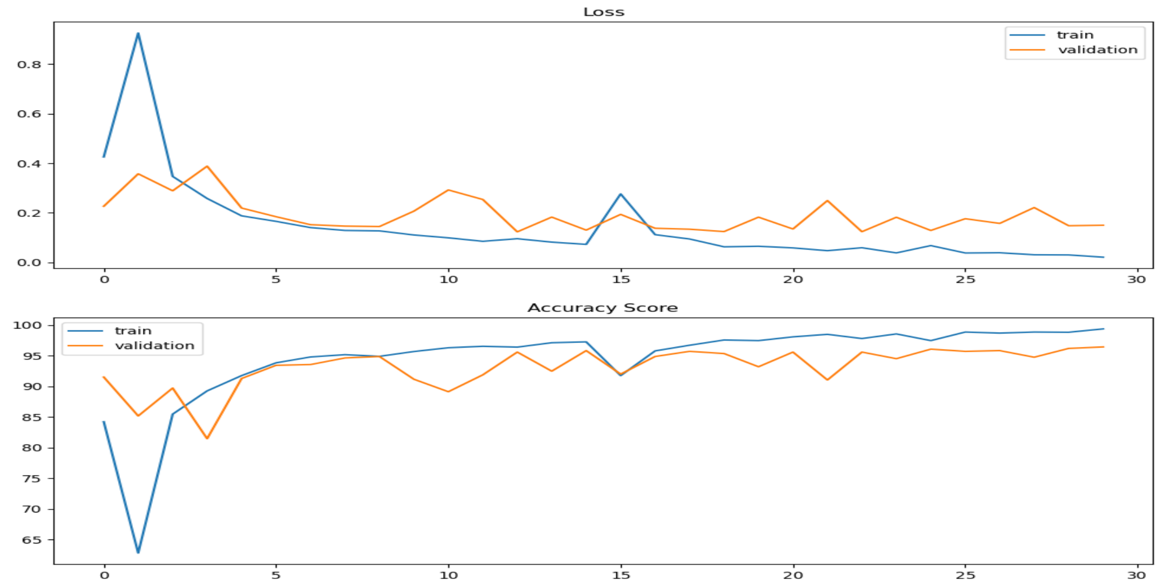


Figure 5: Train accuracy and Loss vs Validation accuracy and Loss

Table 3: Train Vs Validation Accuracy or Loss

Name of the disease	**Parameters**	**Values**
Blight	Number of true positives	100
	Number of samples classified as Common rust	2
	Number of samples classified as grey leaf spot	13
	Number of samples classified as Healthy	0
	Number of false positives	15
	Accuracy	86%
Common Rust	Number of true positives	130
	Number of samples classified as Common rust	1
	Number of samples classified as grey leaf spot	0
	Number of samples classified as Healthy	0
	Number of false positives	1
	Accuracy	99.2%
Grey leaf spot	Number of true positives	54
	Number of samples classified as Common rust	2
	Number of samples classified as grey leaf spot	3
	Number of samples classified as Healthy	0
	Number of false positives	5
	Accuracy	91.52%

Healthy	Number of true positives	117
	Number of samples classified as Common rust	0
	Number of samples classified as grey leaf spot	0
	Number of samples classified as Healthy	0
	Number of false positives	0
	Accuracy	100%
Complete model	True positives	401
	False positives	21
	Accuracy	95.02%

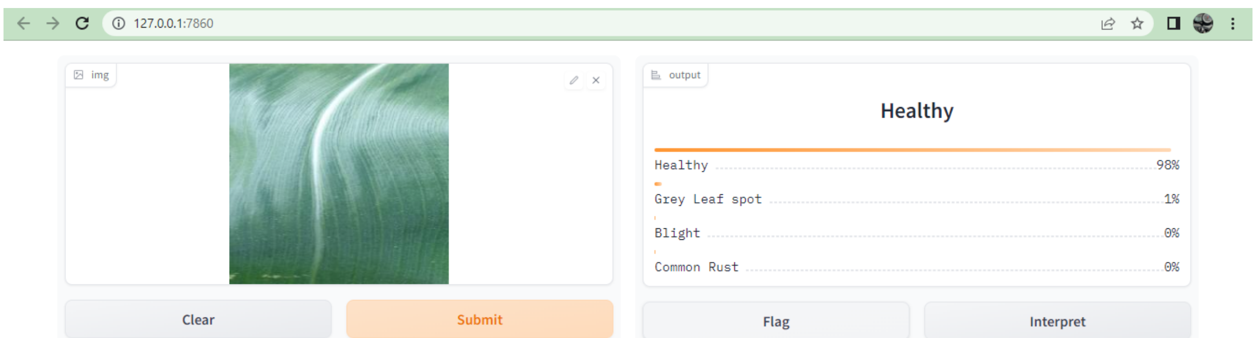


Figure 6: Healthy image classified with confidence score of 99 percentile

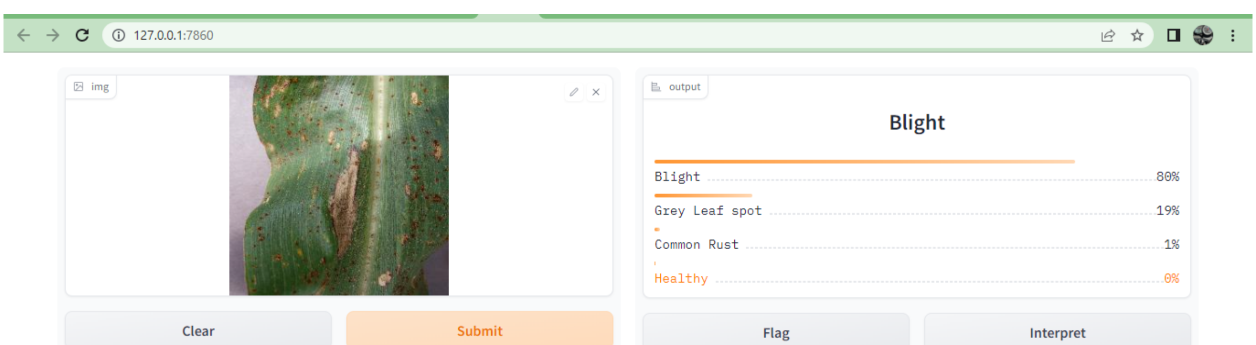


Figure 7: Blight classified with a confidence score of 80 percentile

Figure 8: Common rust classified with a confidence score of 99 percentile

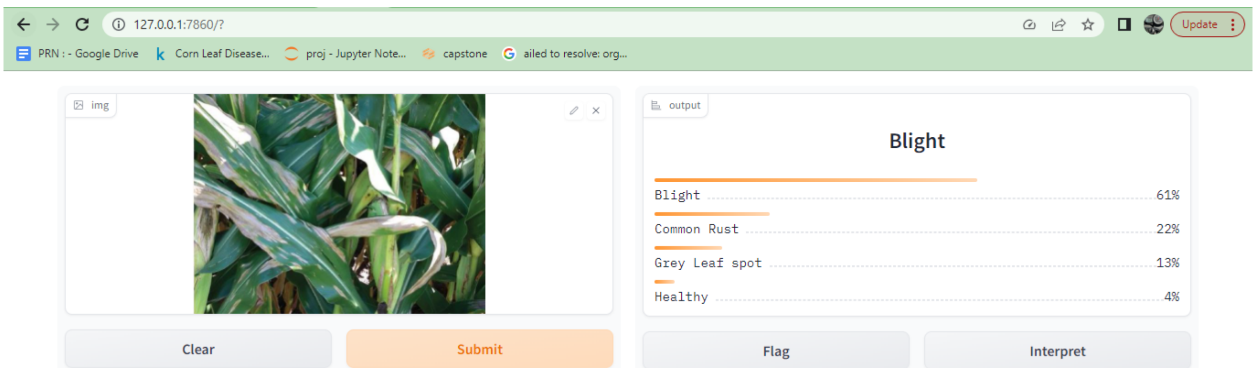


Figure 9: Blight classified with a confidence score of 61 percentile

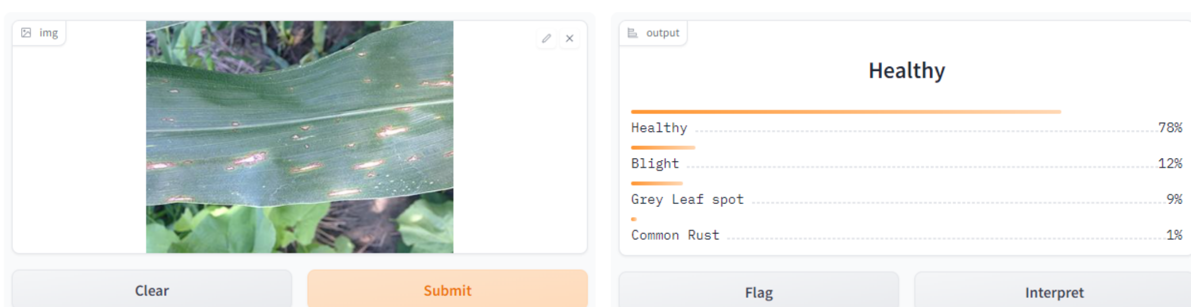


Figure 10: Blight classified as healthy

Table 4 discusses an extensive examination of the established investigation with other existing methodologies.

Table 4: The evaluation of the proposed model against existing methods

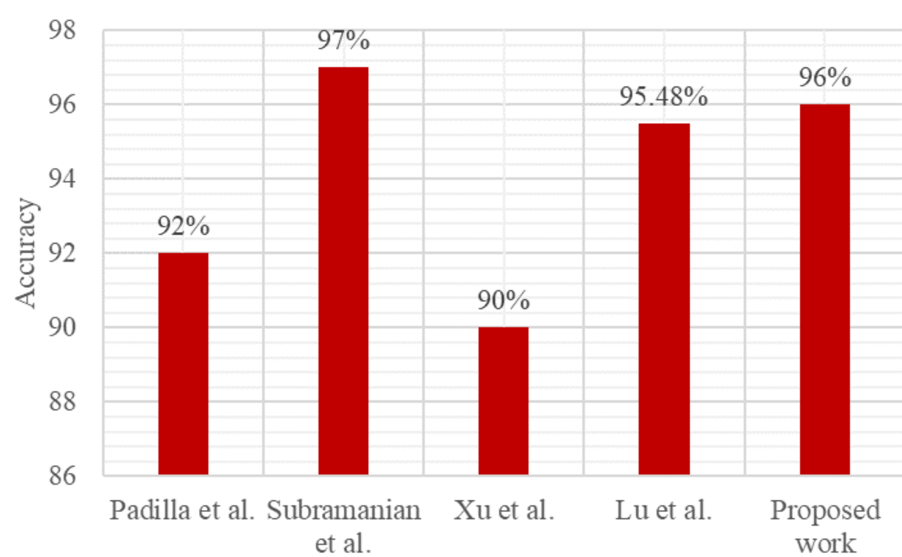
EXISTING APPROACHES	OBJECTIVEs	DATASET QUANTITY	TECHNIQUES	ACCURACY
Padilla-et al.[34]	Classification of three different disease kinds, a healthy type, and an unidentified type	-	CNN employment using OpenMP on a Raspberry Pi	Maximum = 93%
Subramanian-et al.[10]	Classification of three disease kinds, and a healthy type	18,888 images	VGG16, ResNet50, InceptionV3, and Xception	93.92 - 99.9%
Xu et al.[32]	Classification of 3 types of diseases and healthy type	17,600 augmented leaf images	VCGNET-16, Dense net, Resnet 50 and TCI ALEXNET(Modified Alexnet)	90% (mean)
Lu et al.[35]	Identify 10 common rice diseases	500 natural images	Multi-stage-CNN	95.48%
Proposed work	Classification of 3 types of diseases and healthy type	4188 augmented leaf images	Transfer learning on ResNet-18 framework in pytorch and kerras with gradio as frontend	96%

Padilla et al. [34] devised a system using Raspberry Pi as the hardware foundation. Demonstrating the feasibility of creating CNN-based applications with modest hardware, they employed OpenMP to enhance performance. Despite achieving an accuracy of up to 96%, their test accuracy reached only 93%.

Conversely, Subramanian et al. [10] explored multiple approaches to the interaction between two CNN models, EfficientNetB0 and DenseNet121. Their efforts yielded accuracies ranging from 93% to 99.993%.

Lu et al. [35] implemented a method to augment the deep learning capability of CNNs, achieving significant advancements. Their CNN-based model successfully classifies 10 prevalent rice diseases through image recognition, boasting an accuracy of 95.48%.Meanwhile, Xu et al. [32] adapted AlexNet and developed a novel network to construct their CNNs, demonstrating innovative approaches in network architecture design.

The comparison of the proposed model with the existing techniques is given in Figure 11.



Padilla-et al. [34] achieved recognition rates of 93% Leaf Blight, 89% Leaf Rust, and 89% Leaf Spot, respectively well our system achieved an accuracy of 86% for Blight, 99.2% for common rust, and 91.5% for grey leaf spot the mean accuracy is plotted in the above graph. Xu et al. [32] tried out 4 models i.e. VCGNET-16, Dense net, Resnet 50, and TCI ALEXNET, and respectively achieved a mean accuracy of 90%. Subramanian-et al. [10] tried out the experiment in phases and the minimum accuracy achieved was 93% and the maximum achieved was 99%. Lu et al.[35] implemented a technique to enhance the deep learning ability of CNNs and achieved an accuracy of 95.48% whereas our system achieved a mean accuracy of 96% which is better than these existing systems

5.1 Complexity Analysis

- **Model Training:** Using the pre-processed data, the ResNet-18 model is trained. It takes a long time to train a model, according on the epoch count, batch size, and amount of the training dataset. The time complexity is *O(en/b).* if the model is trained for e epochs with a batch size of b and the training collection contains n images. The magnitude of the model parameters and the batch size impact the space complexity. With the model kept in memory during training, the space complexity is ***O(mb)***, where m is the number of parameters.

- **Model Evaluation:** It involves evaluating the trained model on the validation set to measure its accuracy. Size of the validation set and processing time for each image determine the corresponding temporal complexity of the evaluation model. The time complexity is O(m) if the validation set contains m images and processing each image takes O(1) time. Both the size of the validation set and the amount of memory required for keeping the model's predictions determine the space complexity.. Assuming that the predictions are stored in memory, the space complexity is *O(m).*

- **Inference:** It involves using the trained model to make predictions on new images. The time complexity of making predictions depends on the size of the input image and the time taken to process each image. Assuming that each image takes *O(1)* time to process, the time complexity is *O(1)* per image. The space complexity is based upon both the dimensions of the model parameters and the dimensions of the input image.The time complexity, assuming the model is kept in memory during inference, is *O(m+s),* where m is the number of parameters and s is the size of the input image.

The total time complexity of the proposed system is *O(e*n/b)*, where e is the epoch count, n is the picture count, and b is the batch size. Since there are a finite number of parameters in the final model, their magnitude determines the space complexity, which is *O(m).* Number of layers and size of each layer are the major factors that define the time complexity of the DL model used for disease diagnosis. For a single image, the temporal complexity of inference using the ResNet-18 model utilised in this study is $O(n^2)$, where n is the number of layers. The time it takes to handle user queries and react with predictions, process and post-process images, and so on all contribute to the application's time complexity. Gradio can handle multiple user requests concurrently, but the overall response time may depend on the number of concurrent requests and the available resources. The space complexity of the application is mainly determined by the DL model size and the image number that is processed. The ResNet-18 model size is 44 MB, which is relatively small compared to some other deep-learning models. The space required for image pre-processing and post-processing may also depend on the size and resolution of the input images and the number of images being processed concurrently.

6. Conclusion and future works

For both commercial and small-scale farming, corn is a key component of the diets of hundreds of millions of people worldwide. Furthermore, it creates the foundation for numerous industrial goods and biofuels. Yet, the effects of climate change on drought, severe weather, and unseasonably warm temperatures have severely impacted the world's agricultural output. Moreover, plant diseases can destroy maize yields and result in large financial losses. These reasons advance the requirement for incorporating technological advancements in various farming measures to preserve plants and provision farmers with the detection and restrain of diseases. In this paper, we intended to identify common maize illnesses from leaf images using DL algorithms. The performance evaluation's findings show that there is a significant amount of potential for creating and implementing commercial applications that meet the standards for accuracy and usability. Such measures could significantly assist farmers overcome maize diseases and preserve their standard of life. The investigation carried out in this work can be conceivably improved through an enhanced addition process with more images from the dataset's four classifications. Real-world input photos, for instance, could be of any type. of background, which may not be identical to or consistent with the current dataset.

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