Maize Leaves Disease Detection and Classification using AlexNet Model

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Abstract

Crop diseases are a major cause of reduced production and economic losses in the agricultural industry worldwide. To promote human health, it is important to monitor and control these diseases effectively. In the past, image recognition and classification in this field depended on manually designed features created by researchers rather than relying on automated feature extraction methods. The progress made in deep learning has allowed researchers to achieve a significant improvement in the accuracy of detection and classification. Our study utilized a deep-learning framework to classify diseases in maize. Our dataset contains four categories of maize disease. Common rust, Northern Leaf Blight, Cercospora Leaf Spot Grey, and normal. With a 96% accuracy rate, our model proves to be a highly practical solution for safeguarding maize crops against the diseases mentioned earlier, thus providing farmers with a valuable.

Keywords: Software Engineering; Convolution Neural Network; AlexNet; Maize Diseases; Image Classification

Introduction

The major causes of production economic losses in the agricultural industry are crop diseases worldwide. It is very important to monitor and control these diseases efficiently. In the early days, the researchers created and designed manual features for image recognition and classification rather than depending on the automated extraction features. Due to the advancement of deep learning, researchers can achieve a substantial improvement in detection and classification accuracy.

The maize plant is cultivated worldwide for its highly healthful and resourceful grain. Besides rice and wheat, it is the most cultivated crop globally (Huerta-Espino et al., 2011). For over 6,000 years maize crop has been cultivated for and is supposed to have commenced in the fertile fields of ancient civilizations alongside other basic crops. Diseases

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of maize crop have a prominent impact on agricultural yields, resulting in reduced quantity and quality of crop (Weizheng et al., 2008). The common diseases that mostly affect the maize crop are northern leaf blight, Cercospora Leaf Spot Gray and common rust. The researchers often rely on visually observable patterns of the maize plant's leaves in experimental settings in order to gain a better knowledge of these diseases, (Weizheng et al., 2008). Successful crop cultivation on farms needs an effective monitoring of leaf diseases. Experts in the field of agriculture have monitored these diseases manually in the past few days. To perform the disease monitoring with efficiency the experts need to have detailed knowledge in the diverse fields, as well as extensive expertise in recognizing symptoms of disease and grasping their underlying reasons. Farmers might need to travel significant distances to approach expert advice in some developed nations. This process is time-consuming and very expensive. It is very helpful to explore automatic disease detection as it can make it very easy to monitor vast agricultural fields and allow for the automatic recognition of disease marks as soon as they show up on leaves (Rumpf et al., 2010). It is necessary to protect plants from diseases to improve the quality and quantity of crops. Detection and recognition of the specific disease on time is important to choosing the proper treatment and stopping the disease from spreading further (Akhtar et al., 2013; Al-Hiary et al., 2011; Mokhtar et al., 2015).

Maize is a basic food crop that is essential to the world's food security and the livelihoods of millions of people. But several diseases affect the maize crop which can severely lower crop productivity and quality. The manual identification process results in significant productivity losses as this is time-consuming and very costly. Due to recent advancements in the field of machine learning and computer vision, it is possible to develop automated systems for identifying and classifying crop diseases. One of the powerful techniques of the deep learning that shows outstanding results in almost every field along with agriculture is the Convolutional Neural Network (CNN) (Panigrahi et al., 2020).

The main goal of this work is the automatic detection and classification of diseases in maize crop by using CNN. In this work a CNN-based pre-trained (Alex Net) model is used for disease detection and classification, which has already shown good performance in various image classification tasks(Zeb, Arbab, Khan, & Ali, 2023). The proposed system is composed of the following steps: First step is pre-processing in which the background noise and unwanted object has been removed. These pre-processed images were then provided to the Alex Net model to extract the features from these images. Softmax classifier is used to categorize these images based on these four diseases (Arbab, Khan, & Ali, 2022). Apart from other benefits this system will increase the crop yield, cut down the labor cost and efficiently and accurately identify the diseases. The farmers can take necessary actions to control the spread of diseases by receiving the early diseases detection using this system.The main contribution of the proposed work is to:

- design a CNN-based model that is efficient, accurate, and intelligent in detecting and categorizing diseases in maize.
- implement, test, and evaluate the performance and accuracy of the proposed model through a comprehensive set of simulations.

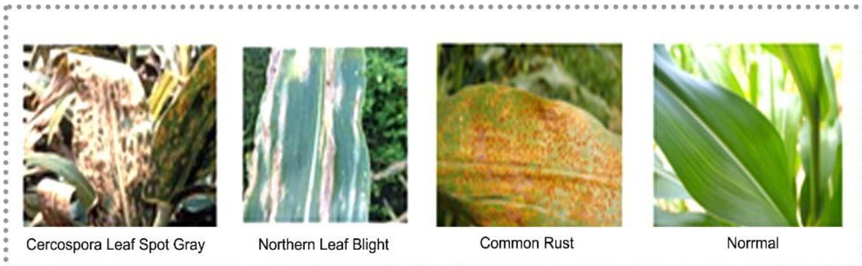

Figure 1 Different Types of Maize Diseases

Literature Review

Computer vision technology has advanced significantly in recent years and is now used in many different industries, including agriculture. To increase crop yield efficiency, crop health monitoring during the growth process has become essential to modern agricultural production. Convolutional neural networks have made significant progress in extracting salient features that are essential for image recognition, thanks to the recent research surge. As a result, numerous CNN architectures that are now well-known in the field were developed, including AlexNet, VGG16, VGG19, GoogLeNet, ResNet, and DenseNet. Applications for these architectures include the detection of plant diseases (Krizhevsky et al., 2017; Simonyan & Zisserman, 2014; Szegedy et al., 2015). In his study, Alehegn (2020) utilized machine learning techniques and imaging to classify corn leaf diseases. The research primarily focused on digital image analysis methods that involve extracting texture, color, and morphology features to distinguish healthy leaves from those affected by maize leaf diseases. A total of 800 images were used in the study, including four classes each containing 200 images. The four classes include: leaf spot, common rust, healthy leaf and leaf blight. A total of 22 features were extracted for each image in the study, and data was classified using Artificial Neural Networks (ANN) and K-nearest neighbors (KNN) classifiers. The results shown that ANN outer perform KNN with an accuracy rate of 94.4%.

Mohanty et al. (2016) train a deep convolutional neural network by using a publicly available dataset consisting of 54,306 plant leaf images. This dataset contained both healthy and diseased. The authors take advantage of AlexNet and GoogLeNet architectures to detect 14 crop species and 26 diseases. The authors achieved a remarkable accuracy rate of 99.35%. Arora & Agrawal (2020) used the Deep Forest architecture, for the classification of maize leaf diseases. The dataset used by the authors consist of four categories, with 100 images in each category. The authors claimed that their proposed approach beat the conventional machine learning techniques such as Random Forest, SVM, KNN and Logistic Regression, classifier in terms of accuracy and performance. The deep forest model was trained with 4 forests, 3 grains and 1000 trees concluding in an accuracy of 96.26%.

Gu et al. (2018) identified the tomato diseases and insect pests by using an improved version of the YOLOv3 algorithm which was significant improvement in the network's performance. The dataset used by the authors consist of 15,000 images and a total of 146,912 bounding boxes which represent 12 different diseases. The authors suggested that our model achieved a mean average precision (mAP) of 92.39% and outer performed the SSD and Faster R-CNN model. This improved version of YOLOv3 network demonstrated remarkable flexibility in complex surroundings by identifying objects with different resolutions and sizes.

Fuentes et al. (2017) introduced a robust deep learning-based detection model for the identification of tomatoes and pests. The authors combined the R-FCN, Faster R-CNN and single shot MultiBox detector with VGG and ResNet after the evaluation. The study's dataset used in this study consist of variations in object size, brightness conditions, and background, including the plant's surrounding area. The authors achieved a mean average precision (mAP) of 85.98%. which indicates that the plain networks outperformed deeper networks, with R-FCN utilizing ResNet-50.

Ferentinos (2018), diagnosed plant diseases by using deep learning models. The authors developed a CNN-based model for detecting and diagnosing plant illnesses using images of both infected and healthy leaves. The model was trained and tested by publicly available dataset and achieved a remarkable accuracy of 99%.

Bedi et al. (2021) developed a model for crop disease detection by using a dataset of 54,306 images of healthy and infected plant leaves. The deep CNN was trained by using this publicly available dataset containing14 different crop species and identifying several diseases. In (Cortes, 2017), a multiclass image processing techniques was developed by the authors to detect various types of plant diseases from a single image.

This multiclass approach can help in the timely identification of diseases, which can help to stop the interventions that can minimize the impact of crop diseases. The authors used a publicly available dataset of 86,147 images containing healthy and infected plants. The dataset was used to train the deep convolutional neural network combined with semi-supervised methods to detect the diseases and classify the crop species.

From the literature review it is clear that the researchers have made a great contribution to in regarding leaf disease and detection, but still there are some challenges that need to be overcome. These challenges include variations in the types and locations of diseases and pests within the image, pattern variations, noisy images, similar backgrounds of objects in the surroundings, and differences in image resolutions, which can make the task more difficult. As a result, we propose a solution to tackle these challenges in the classification and detection of corn leaf diseases.

Proposed Methodology

The proposed methodology involves two main stages: the training stage and the testing stage. The Alex Net model is implied for feature extraction. The dimensions of all the images in dataset were set to 227 x 227 in accordance to comply with the specifications of Alex Net architecture. 70% of data was used for training. For features extraction the convolutional layers were utilized with ReLU and Max Pooling. The extracted features were subsequently fed to the fully connected layers for classification (as shown in Figure 1) to categorize diseases into four distinct classes. The images illustrated in Figure 1 were randomly selected from the dataset. The framework for maize disease classification is presented in Figure 2.

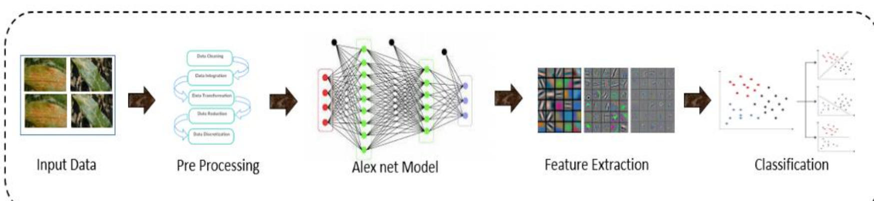

Figure 2: Proposed Methodology.

Pre-Processing

In preparing image data the preprocessing is considered as a very essential step for both performance and technical reasons. For CNN all of the images have to be the same-size arrays which are further processed by fully connected layers. In case of inconsistent image sizes, the performance of the CNN model may not meet prospects. Therefore, preprocessing makes it easier to process and extract the meaningful information by standardizing the size and format of the image data. This is main step to standardize the image size, orientation, and color balance. In this step the images are resized to the size required by the Alex Net model and other techniques are applied to the images such as cropping, normalization and augmentation to enhance the images quality.

AlexNet Model

AlexNet was proposed by Alex Krizhevsk in 2012 composed of 25 convolution layers. The image size of 227 x 227 is recommended for this model. This model applies regularization operation and convolutional pooling to extract very complicated features from the images. Alex Net is comprised of total of 16 layers, which include one input layer, five convolutional layers, five layers for regularization, five down-sampling layers, and three fully connected layers. This architecture allows it to effectively extract sophisticated features from images (Iandola et al., 2016).

Feature Extraction

This is an important step for extracting the meaningful information by decreasing the dimensionality of data. Capturing the essential details and meaningful information from the images are known as features, The main aim of feature extraction is to transform raw data, such as images or text, into a set of meaningful and easily understandable features. Features can correspond to the texture, shape, color, or other characteristics of an image.

Disease Classification

The goal is to train the model to classify images with infected leaves with precision by taking the advantages of patterns and characteristics it has learned from the training dataset. After feature extraction the final stages in the classification process involves using a classifier to assign labels to the input data based on the extracted features. A decision boundary is determined within the dataset to differentiate and separate the various classes during this stage.

Experimental Results and Discussion

In this work for our experimental setup, we use MATLAB. Our experiments focused on analyzing images of maize crops, specifically the leaves, which consisted of both diseased and healthy samples. We can test the accuracy and efficiency of our proposed approach by accurately identifying and classifying the leaves' health of the maize crops.

Dataset

The dataset utilized in this work consists of 4000 images with four categories (Table 1). Specifically, there are three types of diseased leaves and one category that contains images of healthy leaves. The dataset serves as an effective resource for training and testing computer vision models that can accurately classify different types of maize crop diseases along with healthy leaves. Visual Classification of the images of different maize leaves is shown in Figure 3.

Table 1: Details of 4 categories of the Dataset utilized in the proposed work.

S.No.	Four types of Maize diseases	No of Images
1	Normal	1000
2	Cercospora	1000
3	Northern Leaf Blight	1000
4	Common Rust	1000
	Total	4000

Performance Analysis

In performance analysis the accuracy and efficiency of our proposed model is evaluated. This step involves the comparison of output of the given model to known ground truth or reference image to determine the degree of error or deviation from the expected result. The common metrics used for measuring the performance of any image processing model are F1-Score, recall and accuracy. Apart from the accuracy the performance analysis also includes analyzing the computational cost and speed of the algorithm. It also includes the complex image processing tasks that how an algorithm can handle the complex and large datasets. The efficiency of the proposed system can be calculated by analyzing its overall accuracy and loss score, both of which can be calculated using the test dataset. The proposed technique was evaluated using the following equations:

$$\text{Precision} = \left(\frac{\text{TP}}{\text{TP+FP}}\right) \tag{1}$$

$$\text{Recall} = \left(\frac{\text{TP}}{\text{TP+FN}}\right) \tag{2}$$

$$\text{Accuracy} = \left(\frac{\text{TP+TN}}{\text{Total No of Images}}\right)100 \tag{3}$$

$$\text{F1} - \text{Score} = \left(\frac{2*\text{precision}*\text{recall}}{\text{precision+recall}}\right) \tag{4}$$

The equations mentioned above incorporate several parameters, including FPR, FNR, FP, TN, FN, and TP, which stand for False Positive Rate, False Negative Ratio False Positive, True Negative, False Negative, and True Positive, respectively. When images are detected, there is a possibility of misclassifying them into a different category than their actual class.

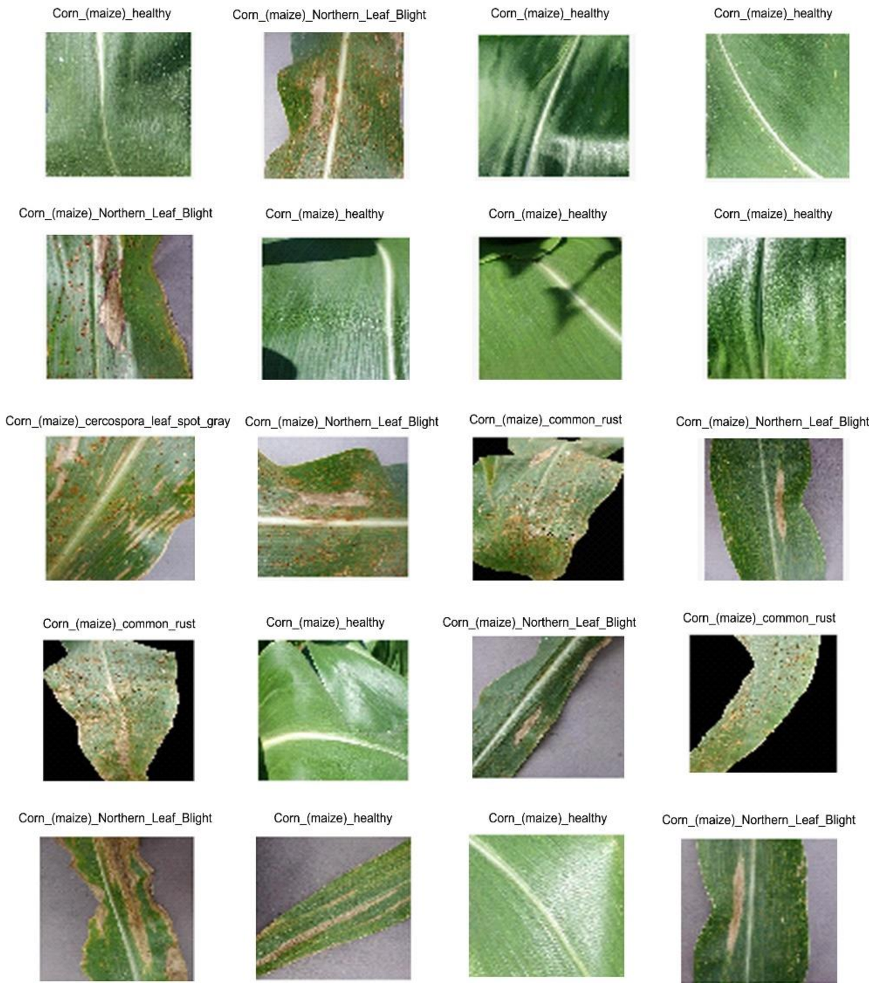

Figure 3 Visual Classification

In machine learning performance evaluation includes measuring the accuracy of a model, which shows how often the algorithm correctly classifies a data point. In this research, the model achieved an accuracy of 96%, which means that the model accurately predicted 96 out of every 100 data points. In machine learning loss accuracy refers to the difference between the actual and expected output values of the model. The model has better accuracy if the loss is low and if the loss is high, it means that the model is making mistakes on the given dataset. Figure 4 shows the loss and accuracy of the proposed model. The ratio of the loss is 4%, which specifies the model errors in prediction.

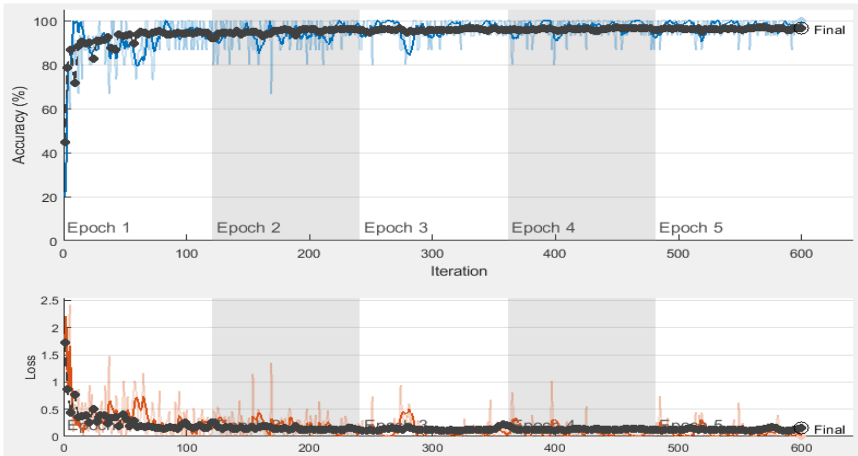

Figure 4 Final Results

The effectiveness and efficiency of our proposed approach is evaluated by measuring its accuracy and comparing it with the current two solutions (KNN and Ensemble methods). The results in Figure 5 show that our proposed approach achieved the accuracy of 96 % which perform better than the KNN (80%) and ensemble methods (84 %). In general, these results shows that our proposed system is more effective than the other methods in identifying the diseases in maize crops with high accuracy.

The performance of three classifiers (Ensemble, KNN, and Proposed CNN) on a classification task was evaluated based on their accuracy and F1-Score. The Proposed CNN achieved the highest accuracy (0.95) and F1-Score (0.96), indicating its strong performance in correctly classifying data points and maintaining a balance between precision and recall. The Ensemble method, while having a lower accuracy (0.79) and F1-Score (0.84) than the Proposed CNN, outperformed KNN, which had the lowest accuracy (0.76) and F1-Score (0.80) among the three classifiers. These results suggest that the Proposed Technique is the most effective classifier, followed by the Ensemble method, with KNN being the least effective.

Unlike most prior research using transfer learning on diverse plant data, our study's targeted focus on maize enabled the use of a AlexNet model delivering superior accuracy while at the same time minimizing both computational requirements and model complexity. This research explored the use of deep learning for maize crop disease detection. Current deep learning convolutional neural networks (CNNs) like AlexNet, was evaluated for its performance. This model achieved 95% accuracy in identifying 4 maize crop diseases (including healthy crops). This research reveals the capability of deep learning for the maize crop disease detection accurately, which can grant farmers and contribute to improved agricultural production. This work makes it indicating for practical implementation in real-world agricultural settings. The research used large datasets of maize crop images, which helped achieve high accuracy. This stage involves comparing the models used in past studies. In Table 2, we have to look at the models that were employed in past studies and in this study, ranked by a performance from worst to best.

Table 2 Classifiers Performance based on different metrics.

Classifiers	Accuracy	Recall	F1- Score
Ensemble	0.79	0.89	0.84
KNN	0.76	0.86	0.80
Proposed (AlexNet)	0.95	0.96	0.96

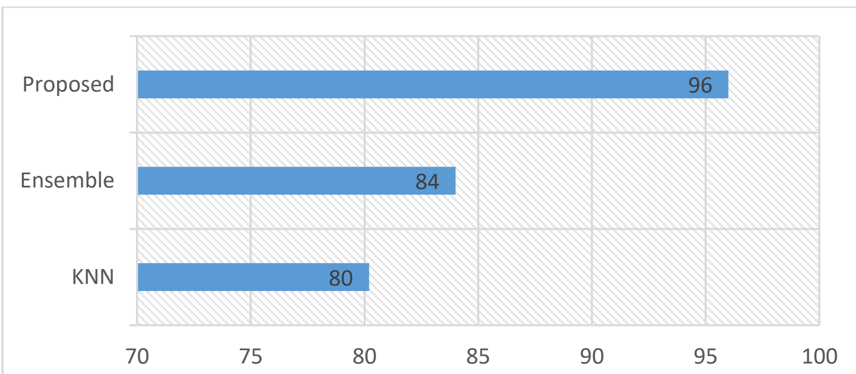

Figure 5 Comparative Analysis

Conclusion and Future Work

Maize crop is a basic crop and is consumed worldwide. This crop is most susceptible to the many diseases which is difficult to identify using conventional laboratory methods or just by observing the leaves symptoms. In this work we have used a deep learning model to accurately identify the maize crop diseases with high accuracy of 96% which outer performs than the other existing approaches for detecting maize crop diseases.

In future, we can add more diseases of maize crop and other crop varieties and use different preprocessing techniques. Furthermore, we can implement this model on any edge device like drone and mobile to detect the maize diseases in real-time to evaluate its practical effectiveness.

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