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Deep SqueezeNet learning model for diagnosis and prediction of maize leaf diseases

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Abstract

The maize leaf diseases create severe yield reductions and critical problems. The maize leaf disease should be discovered early, perfectly identified, and precisely diagnosed to make greater yield. This work studies three main leaf diseases: common rust, blight, and grey leaf spot. This approach involves pre-processing, including sampling and labelling, while ensuring class balance and preventing overfitting via the SMOTE algorithm. The maize leaf dataset with augmentation was used to classify these diseases using several deep-learning pre-trained networks, including VGG16, Resnet34, Resnet50, and SqueezeNet. The model was evaluated using a maize leaf dataset that included various leaf classes, mini-batch sizes, and input sizes. Performance measures, recall, precision, accuracy, F1-score, and confusion matrix were computed for each network. The SqueezeNet learning model produces an accuracy of 97% in classifying four different classes of plant leaf datasets. Comparatively, the SqueezeNet learning model has improved accuracy by 2–5% and reduced the mean square error by 4–11% over VGG16, Resnet34, and Resnet50 deep learning models.

Keywords SqueezeNet, Deep learning, Maize leaf disease, Resnet

Introduction

The Indian population's primary source of income comes from agriculture, which is also the country's primary support system for the largest industry. As agronomy production reduces, the demand for food is increasing dramatically. Farmers, scientists, researchers, analysts, specialists, and the government work together to develop new techniques that will enhance agricultural production to meet demand. With the aid of technology, the agriculture industry has made significant achievements. Farmers are having issues due to various conditions, including global climate change and plant diseases. Several causes for the decrease in crop yield result in the farmer's economy. The work of determining the quality of the crops through manual examination is difficult since it requires a lot of time, accuracy, and money.

Along with rice and wheat, maize is one of the most significant food crops in India. It offers a significant supply of carbohydrates for people. In addition to this, it is grown for animal feed, flour, cooking oil, and raw materials for creating furfural. Bacteria, fungi, nematodes, and viruses are the main factors that can cause illnesses in maize (because of nutrient deficiency, humidity, and temperature). The leaves, fruits, and stems are the primary targets of maize diseases. Researchers have developed several remedies for this issue by creating new technologies, including object detection, and image processing for quality evaluations.

Plant leaf diseases cause yield reductions that directly affect the domestic and international food production systems and cause financial losses. The Food and agriculture organization states that pests and plant diseases cause a 20–40% loss worldwide in food output [1]. With the evolution of image recognition, agricultural technology is being used more extensively to identify and categorise the quality of agricultural products [2]. A reliable supply of good quality food is dependent on sophisticated agricultural technology. Due to pests and diseases, farmers only harvest a few crops annually. Farmers may enhance production and profit while spending less time and money on inputs according to automated crop health detection [3]. Traditional machine learning techniques are being used more and more frequently in predicting plant leaf diseases because of the quick advancement of computer technology. Farmers can use artificial intelligence-based disease recognition systems to detect and prevent the disease in its early stages by analysing the images of the stems and leaves of the plants [4].

One of the leading grain crops, maize, suffers significantly from maize leaf diseases in terms of productivity and quality. Multiple symptoms of maize leaf diseases might result in various rapid predictions and precise diagnoses of leaf disease. Such methods include support vector machines (SVM), neural network methods, and digital image processing, effectively employed to identify and categorise leaf diseases. Maize crops can be damaged for various reasons, including natural disasters or insects. To recognise and classify maize disease lesions and gauge their severity in challenging field settings, precise disease management techniques must be developed. Despite the growing popularity of deep learning approaches for detecting diseases, there are still problems for the reliable approaches for detecting numerous diseases in real-world.

Related works

More academics and industry professionals have recently begun investigating how to recognise crop diseases that impact the crop field. The categorization of leaf diseases can be accomplished using a variety of techniques, including neural networks [5], and support vector machines [6, 7]. From a variety of input images, it may derive meaningful feature representations. Deep learning can quickly and accurately identify crop infections to achieve agricultural disease prevention. It increases the precision with which plant diseases may be identified and broadens the potential uses of computer vision in smart agriculture. In the area of recognition, deep learning has achieved some remarkable achievements [8]. This study employs convolutional neural networks (CNN) assisted principles to model a maize leaf disease image detection and categorization network. A CNN network categorized the leaf diseases obtained using a smartphone camera was trained using Neuroph [9].

The Select Kernel Point Swish Net-50 CNN model is suggested in this study to accurately identify maze leaf illnesses in natural scene photos. The loss function has been used in this work to direct the model's parameter adjustments to address the imbalance issue. With an accuracy of 92.9%, the suggested model is more successful at identifying maize leaf disease [10]. The Cifar10 and GoogLeNet models each obtain an average accuracy of 98.8% and 98.9% when recognizing eight different types of maize leaf diseases. Reduced convergence iteration and potential improvement to maize leaf disease accuracy are two benefits of the revised approaches, which can also increase the effectiveness of model training and identification [11].

Studies have demonstrated that the Robust Alexnet identification system may be improved by using the maize leaf disease feature augmentation method. This approach exhibits significant resilience for images of maize disease captured in the natural setting, serving as a guide for diagnosing plant leaf diseases [12]. This research focused on supervised machine-learning methods that employ leaf images to detect maize plant diseases. The Random Forest algorithm achieves an accuracy of 79.23% compared to other categorization methods [13]. This study creates a transmission module to link the detection module with the fine-tuning network. To further improve the model's detection capabilities, switch the loss function to a generalized intersection over the union. The maximum precision reaches 91.83% after 60,000 iterations [14].

This study investigated textural features based on grey-level co-occurrence matrices for classifying maize leaf diseases using different multiclass support vector machine configurations. The average best accuracy of classification utilising the set of characteristics was 83.7% [15]. To expedite training, it employs learning and a warm-up technique. Therefore, three types of maize leaf diseases, including blight, rust, and maculopathy, may be effectively and precisely recognised. The validation set showed that the suggested strategy has a 97.41% accuracy rate [16]. The hyperparameters are chosen via Bayesian optimization, and augmentation is employed to increase the model's generalizability. Analysis and comparison of the suggested models are included in the work. The findings show that all trained models can classify maize leaf diseases with more than 93% accuracy [17].

This research investigates the AlexNet model [18] for rapid, precise diagnosis of maize leaf diseases. This model produced an accuracy of 99.16%, utilising several iterations, including 25, 50, 75, and 100. For the maize dataset from PlantVillage, the model's average accuracy was 99.44%, and training took 123 iterations [19]. This study's classification of leaf diseases of maize plants is done by applying a modified deep CNN architecture. The CNNs are evaluated to differentiate between four classes (one healthy class and three disease classes) and have a 97.89% precision rate [20].

The four types of corn leaf images are trained and tested using the upgraded CNN model, which is made possible by adding the Adam optimizer, modifying the pooling operations, parameters, and fewer classifiers. This model achieves an accuracy of 98.78% on average while detecting three different types of corn leaf diseases [21]. The Gaussian quantum particle swarm optimised recurrent neural network beat previous features built deep image transfer networks in predicting Cercospora leaf spot damage, with RMSE of 6.290, R2 of 0.949 [22]. Contrasted to models evaluated using idealised datasets, the deep learning models utilising genuine mixed diseases field data achieve higher generalizability and external validity [23].

The collected unhealthy images of maize were used to train three various image neural networks including the Inception-v3 network. The top-performing model on a separate test dataset had an average recall of 95.96% and a classification precision of 95.99% [24].

This paper proposed the categorization of diseases with EfficientNet architecture, and the model was evaluated against other models. The findings discovered that EfficientNet B4 and B5 models produced better accuracy and precision rates of 99.97% and 99.91% [25]. Three different architectures—ResNet50, InceptionV3, and ResNet152V2—are taken into consideration as the study's framework. The ResNet152v2 model performs the best on the test set. The issue is analysed by three measurements—accuracy, review, and the precision disarray metric. The best outcomes are obtained by the ResNet152 model, which has an accuracy and precision of 0.984 and 0.91, respectively [26]. The test samples of the Common Rust condition were then automatically classified into the four severity classes using a VGG-16 network that was trained using the four severity classes. The accuracy of validation and testing was 95.63% and 89% for the VGG-16 network trained using the suggested method's images [27].

The Deep Forest technique and automated innovative strategy for accurate classification represents a considerable improvement above manual classification as it currently stands and other, less accurate techniques. The suggested strategy has performed more accurately than Deep Neural models and conventional machine learning techniques [28]. A dataset with 54,306 images of healthy and damaged plant leaves captured in regulated environments, the author trained a deep CNN to recognize 26 illnesses and 14 crop species. The model accuracy of 99.35% provides evidence that this approach is effective [1]. The author showed how a system could reliably and automatically detect lesions caused by northern leaf blight in images of maize plants taken in the field. The system had an accuracy rate of 96.7% on test data not utilized in training [29].

With the help of the author's thorough description and user-friendly taxonomy of machine learning tools, the plant community can apply the best-practice guidelines and ML tools appropriately and simply for a variety of biotic and abiotic stress features [30]. The proportion of leaf area with disease lesions was calculated to determine the severity. The combined (UNet-DeepLabV3+) model successfully predicts, which indicates that the predictions were fairly accurate [31].

The data collection used in this work, which consisted of 329 sunflower images categorized into five groups and was created with Google Images, is used in the work. The suggested model is compared to existing deep learning models based on accuracy using the same data set as the initial comparison [32]. This work proves the potential of merging unmanned aerial vehicle with the support of deep learning to produce better throughput and accurate assessments of plant diseases. The mean intersecting over the union between the predicted lesions and ground truth was 0.73, and the average accuracy was 0.61 across the range of intersecting over union thresholds (0.50 to 0.95) [33].

The authors in [34] build a probabilistic programming methodology for plant disease diagnosis using Bayesian deep learning techniques. According to the findings, Bayesian inference can optimize deep learning models to produce classification performance that is on par with conventional optimization techniques [34]. The processing stage and the image analysis stage of the suggested algorithm were both implemented. The images were initially transformed into binary images in which the maize leaves were separated from the other pixels. The images were separated into blocks at the second stage and labelled as "damaged" or "nondamaged," depending on how many objects were discovered in each block. The algorithm successfully categorized 94.72% of the 720 images [35].

Supervised Machine Learning techniques were applied in this study to forecast diseases in maize plants, employing YOLO architecture for segmentation and the discrete wavelet transform for feature extraction. This research demonstrates [36] that the support vector machine produces better results. This study [37] proposed a mixed loss function using a central cost function to enhance lesion detection accuracy. Four pre-trained convolution structures in Faster R-CNN were optimized with random gradient descent, with M-Faster R-CNN using VGG16 convolution layers. It demonstrated superior performance in maize disease detection, offering timely prevention and control. The work in [38] highlights the challenges posed by diseases like Northern Leaf Blight (NLB), emphasizing the need for early detection. Using a deep learning-based Attention U-Net model, the study achieved superior NLB disease segmentation results with an average pixel-wise F1 score of 85.23%.

Proposed methodology

The schematic diagram of the proposed methodology has been depicted in Fig. 1. The maize plant dataset is accessible on the Kaggle repository [39], notably for images of maize leaf disease. It consists of four subsets of diseases with a total of 4188 images, with 1306 images for common rust, 574 images for grey leaf spot, 1146 images for northern leaf blight, and 1162 images for healthy. The pre-processing, imager augmentation, image sampling and labelling have been done on the maize dataset. Then the deep SqueezeNet learning model was applied, and its performance was evaluated with various metrics [40]. The training and testing of the disease classification are done using these labelled images. Starting with the training phase and continuing through the evaluation of the effectiveness of recognition algorithms, a proper dataset is necessary at every

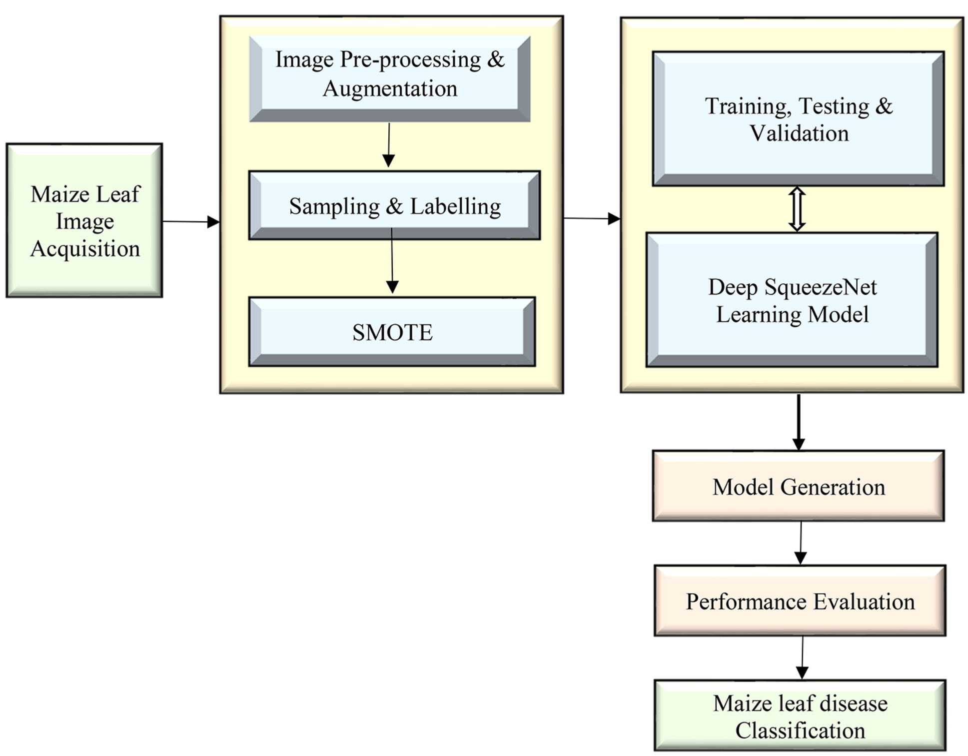

Fig. 1 Schematic diagram of the proposed work

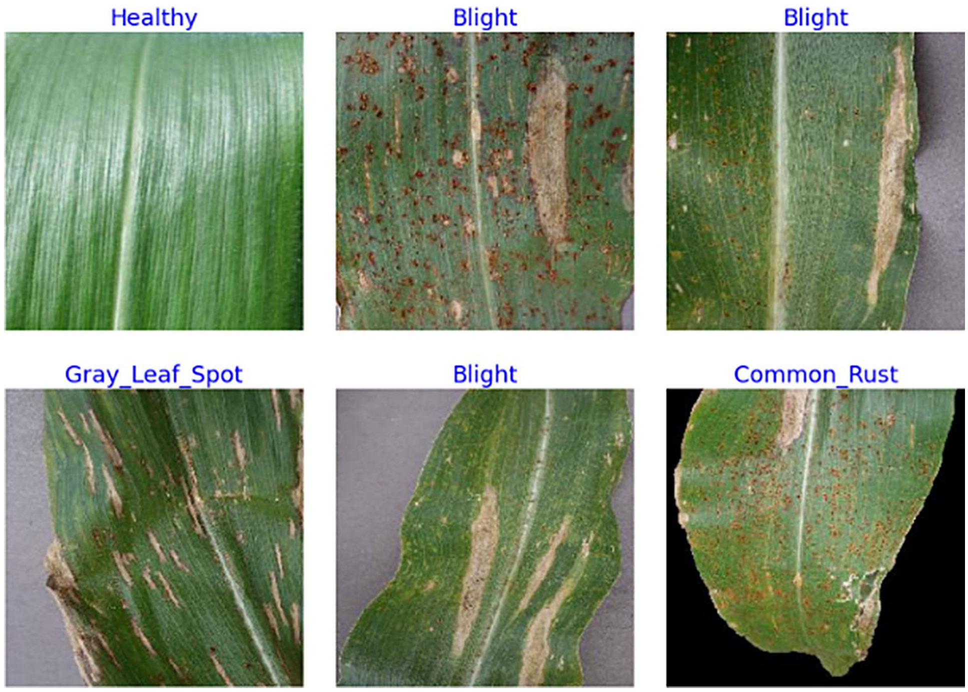

Fig. 2 Maize leaf disease categories

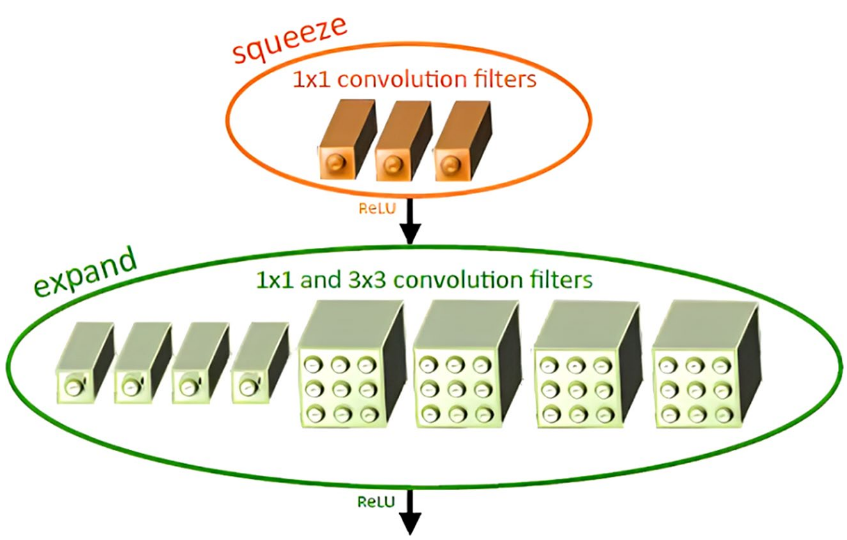

Fig. 3 Fire module of SqueezeNet

stage of disease identification research. The infected maize leaves are divided into three categories, and healthy leaves are in a separate category. Figure 2 depicts different types of diseases that affect maize leaves. The primary diseases examined in this study were common rust, grey leaf spot, and northern leaf blight.

Augmentation

CNN training requires a large amount of data. The CNNs can acquire more features, the more data they have to learn from. It is required to enhance the dataset using various techniques to distinguish between the various disease categories because the initial leaf image dataset that was obtained for this study is insufficient. The additional versions are made after the initialised original images are rotated 270, 180, and 90 degrees, cutting the centre of the image by the same amount, mirroring each rotational image, and turning all processed images into grayscale. The strategies mentioned above increase the dataset, which reduces over-fitting in the training phase [30]. The maize leaf dataset consists of 4188 images in total, of which 80% were used for training and 20% for testing.

Image pre-processing and labelling

Before the model is trained, the maize leaf images in the dataset for the deep CNNs classifier are pre-processed to enhance consistency and feature extraction. The normalisation of image size and format is one of the most important activities. All images used in this study are automatically scaled to 32×32 dots per inch and 224×224 pixels using Python programmes built on the OpenCV framework. Agricultural professionals looked at leaf images sorted by a search of keyword. They classified the images with the correct disease term to verify the accuracy of the classes in the dataset. It is well acknowledged that using correctly identified images for the validation and training dataset is crucial. Only then can a suitable and trustworthy model be created. SMOTE is a sampling technique used to solve classification issues with unbalanced class distribution in the maize leaf images. This approach's primary aspect is to combine oversampling minority class (i.e. grey leaf spot with 574 images), with undersampling the frequent classes. The key objective of SMOTE is to precisely predict rare extreme values in the images.

Deep SqueezeNet

In the proposed work, the deep SqueezeNet Model has been implemented for disease detection of maize leaves. The deep SqueezeNet model concentrates on precision with fewer parameters, and this model design emphasizes greater precision than other Convolutional neural network models. The transmission overload between the servers will be lowered in this approach. SqueezeNet's architecture focuses on three techniques to decrease the number of factors in the network. These techniques include changing 3×3 filters to 1×1 filters, downsampling the network, and reducing the number of input channels to 3×3 filters, enabling the convolution layers to have substantially activated maps.

The SqueezeNet is dependent on various "Fire Layers" each of which includes "Fire-Modules" as seen in Fig. 3. A Fire Module is made up of an expanded layer with a mixture of 3×3 and 1×1 convolution filters that is fed into a squeeze convolution layer with just 1×1 filters. There are three hyperparameters in a Fire Module: (i) sq1×1, ex1×1, and ex3×3, (ii) ex1×1 and ex3×3: Expand Layer 1×1 and 3×3 filters, (iii) sq1×1: Squeeze Layer of 1×1 filter. Figure 4 gives the proposed SqueezeNet architecture. Agreed with the reviewer. SqueezeNet stands out due to its architecture, which is designed for efficiency and accuracy in deep image analysis.

It incorporates fire modules, which consist of a squeeze layer (performing dimensionality reduction through 1×1 convolutions) followed by expand layers (using both 1×1 and 3×3 convolutions). This design significantly reduces the number of parameters compared to traditional architectures like VGG16 or ResNet while maintaining competitive accuracy levels. The proposed SqueezeNet, a deep neural network architecture designed with 13 convolutional layers. These layers are arranged into squeeze and expand layers

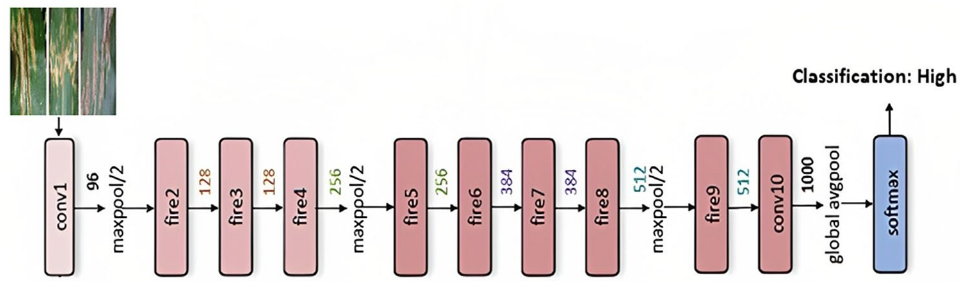

Fig. 4 SqueezeNet

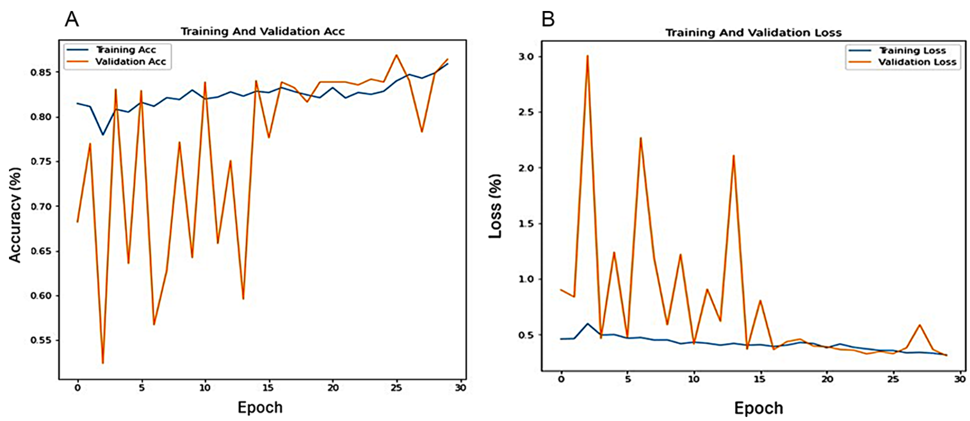

Fig. 5 (**a**) Training/Validation Accuracy. (**b**) Training/Validation Loss

Table 1 Performance Scores of SqueezeNet

	Precision	Recall	F1-Score
Blight	0.95	0.95	0.95
Common Rust	0.97	0.98	0.98
Gray Leaf Spot	0.96	0.93	0.94
Healthy	1	1	1
Accuracy	0.97		

Table 2 Performance scores of VGG

	Precision	Recall	F1-Score
Blight	0.9	0.84	0.87
Common Rust	0.98	0.97	0.98
Gray Leaf Spot	0.69	0.81	0.75
Healthy	1	1	1
Accuracy	0.92		

that make up fire modules. SqueezeNet is able to attain a fair balance between model size and accuracy through the incorporation of these fire modules.

Results and discussions

The proposed deep SqueezeNet learning algorithm has been developed and evaluated with a system configuring 6 GB RAM, an Intel i3 processor, and Python libraries. The maize leaf dataset has been divided into training and testing with 80% and 20%, respectively, with k-fold cross-validation of 10. The training accuracy, validation accuracy, training loss, and validation loss are depicted in Fig. 5(a) and Fig. 5(b). The results of the proposed work are analysed using accuracy, f1-score, precision, confusion matrix, and recall [41, 42].

Table 1 gives the SqueezeNet-based maize leaf prediction performances of precision, recall, and f1-score. The blight, common rust, grey leaf spot and healthy leaves are predicted using the SqueezeNet-based proposed model with the precision rate of 0.95, 0.97, 0.96, and 1, respectively. The SqueezeNet-based proposed model predicts the blight, common rust, grey leaf spot and healthy leaves with the recall value of 0.95, 0.98, 0.93, and 1, respectively; similarly, the F1-score are 0.95, 0.98, 0.94, and 1 respectively. It gives an accuracy of 0.97 for the prediction of blight, common rust, grey leaf spot and healthy leaves.

Figure 6 depicts the confusion matrix of the proposed SqueezeNet model over a test set, where a total of eight maize leaf diseases are misclassified. The blight, common rust, grey leaf spot and healthy leaves are accurately classified as 51, 62, 23, and 55 over a test set of maize leaf images.

Table 2 gives the VGG16-based maize leaf prediction performances of precision, recall, and f1-score. The blight, common rust, grey leaf spot and healthy leaves are predicted using the VGG16 model with the precision rate of 0.9, 0.98, 0.69, and 1, respectively. The VGG16 model predicts the blight, common rust, grey leaf spot and healthy leaves with the recall value of 0.84, 0.97, 0.81, and 1, respectively; similarly, the F1-score are 0.87, 0.98, 0.75, and 1, respectively. It gives an accuracy of 0.92 for the prediction of blight, common rust, grey leaf spot and healthy leaves.

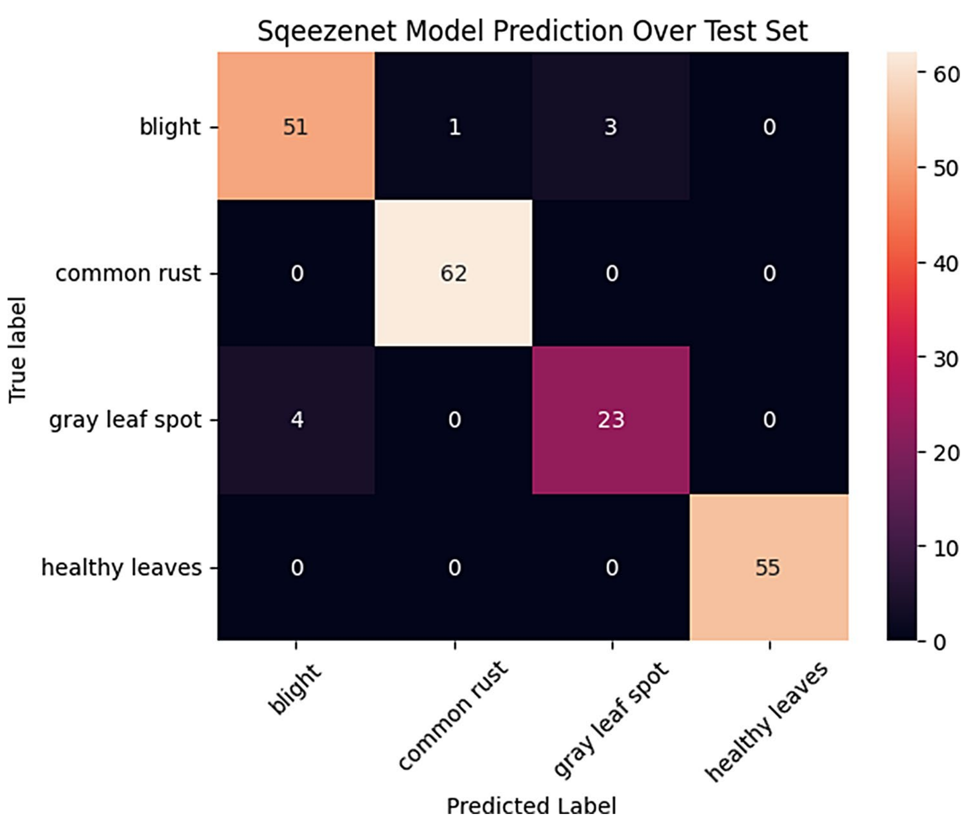

Fig. 6 Confusion matrix of SqueezeNet

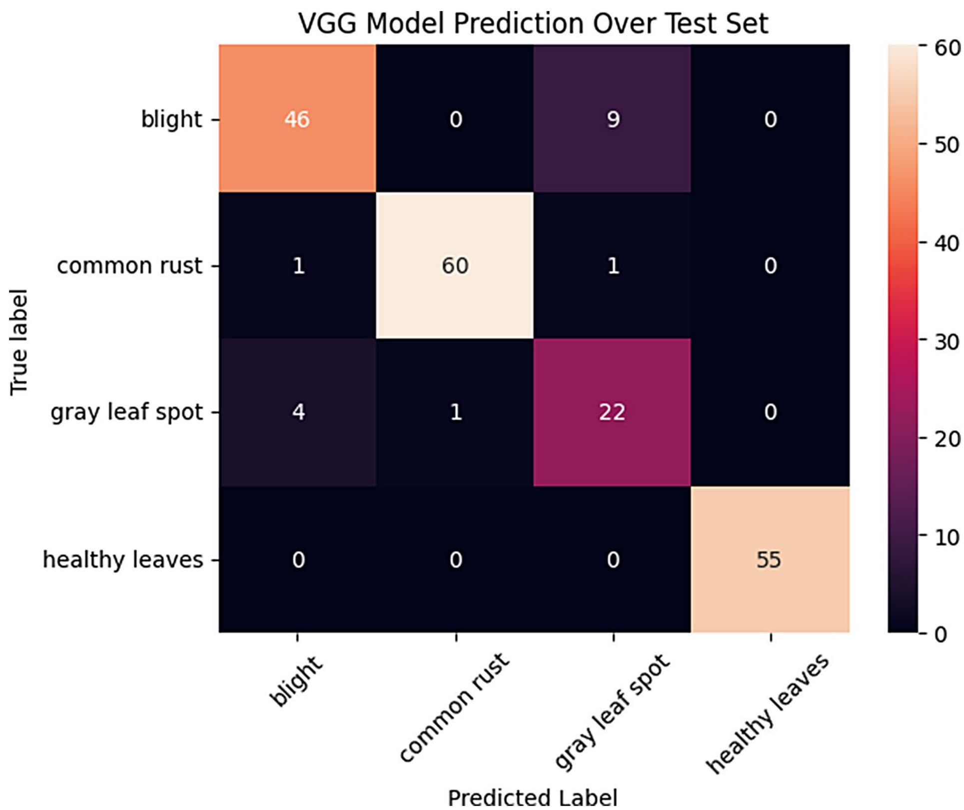

Fig. 7 Confusion matrix of VGG

Table 3 Performance scores of Resnet34

	Precision	Recall	F1-Score
Blight	0.94	0.9	0.92
Common Rust	0.97	0.98	0.98
Gray Leaf Spot	0.84	0.91	0.88
Healthy	1	1	1
Accuracy	0.95		

Figure 7 depicts the confusion matrix of the VGG16 model over the test set, where a total of 16 maize leaf diseases are misclassified. The blight, common rust, grey leaf spot and healthy leaves are accurately classified as 46, 60, 22, and 55 over the test set of maize leaf images.

Table 3 gives the Resnet34-based maize leaf prediction performances of precision, recall, and f1-score. The blight, common rust, grey leaf spot and healthy leaves are predicted using the Resnet34 model with precision rates of 0.94, 0.97, 0.84, and 1, respectively. The Resnet34 model predicts the blight, common rust, grey leaf spot and healthy leaves with the recall value of 0.9, 0.98, 0.91, and 1, respectively; similarly, the F1-score are 0.92, 0.98, 0.88, and respectively. It gives an accuracy of 0.95 for the prediction of blight, common rust, grey leaf spot and healthy leaves.

Figure 8 depicts the confusion matrix of the Resnet34 model over the test set, where a total of 12 maize leaf diseases are misclassified. The blight, common rust, grey leaf spot and healthy leaves are accurately classified as 51, 60, 23, and 56 over a test set of maize leaf images.

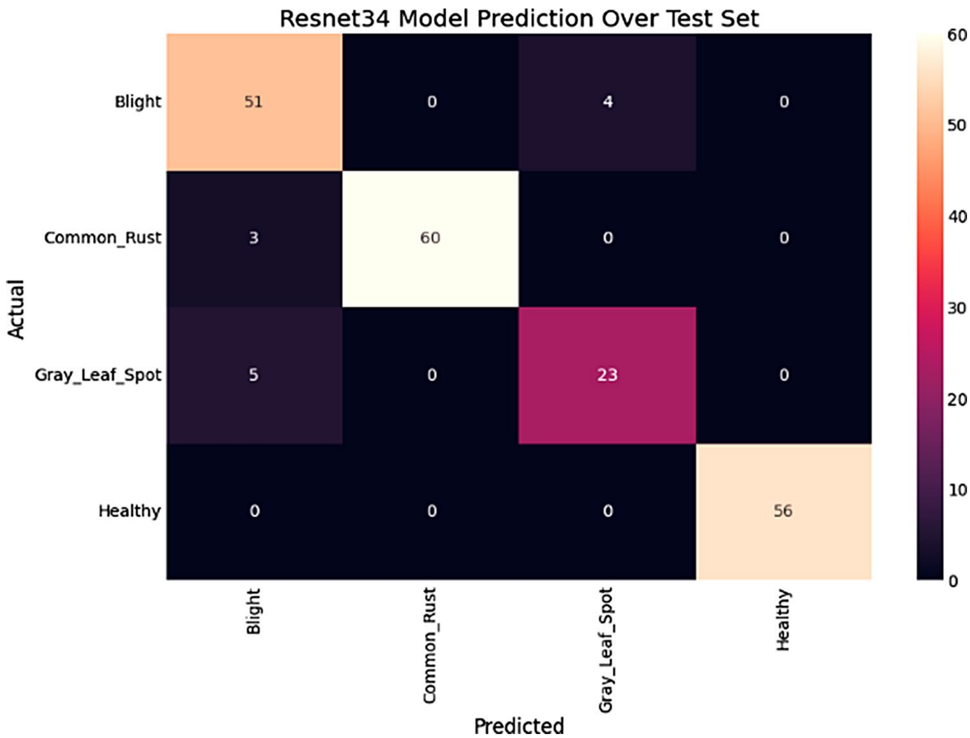

Fig. 8 Confusion matrix of Resnet34

Table 4 Performance scores of Resnet50

	Precision	Recall	F1-Score
Blight	0.89	0.93	0.91
Common Rust	0.98	0.97	0.98
Gray Leaf Spot	0.85	0.81	0.83
Healthy	1	1	1
Accuracy	0.94		

Table 4 gives the Resnet50-based maize leaf prediction performances of precision, recall, and f1-score. The blight, common rust, grey leaf spot and healthy leaves are predicted using the Resnet50 model with the precision rate of 0.89, 0.98, 0.85, and 1, respectively. The Resnet50 model predicts the blight, common rust, grey leaf spot and healthy leaves with the recall value of 0.93, 0.97, 0.81, and 1, respectively; similarly, the F1-score are 0.91,0.98, 0.83, and 1, respectively. It gives an accuracy of 0.94 for the prediction of blight, common rust, grey leaf spot and healthy leaves.

Figure 9 depicts the confusion matrix of the Resnet50 model over the test set, where a total of 11 maize leaf diseases are misclassified. The blight, common rust, grey leaf spot and healthy leaves are accurately classified as 51, 60, 22, and 55 over a test set of maize leaf images.

Figure 10 gives the comparative accuracy scores of VGG16, Resnet34, resnet50, and the proposed SqueezeNet models. It can be clearly seen that the proposed SqueezeNet model produces 2–5% of accuracy. Table 5 represents the Mean Square Error (MSE), Root MSE (RMAE), and Mean Absolute Error (MAE) of proposed SqueezeNet and other compared deep learning models. The proposed SqueezeNet model produces a

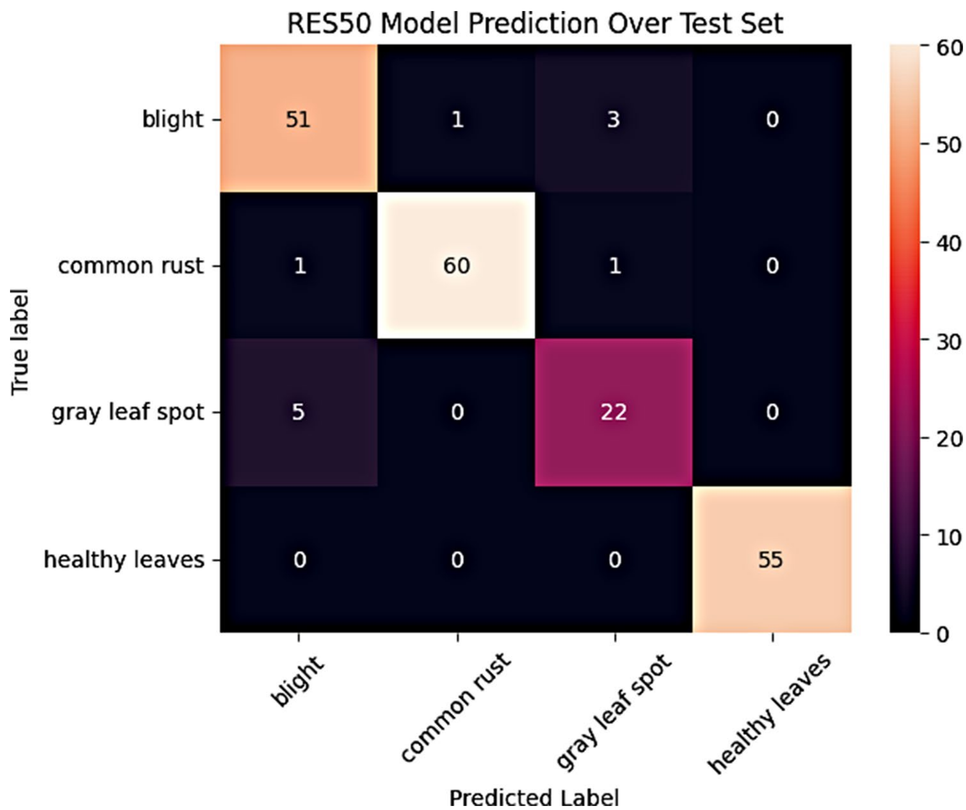

Fig. 9 Confusion matrix of Resnet50

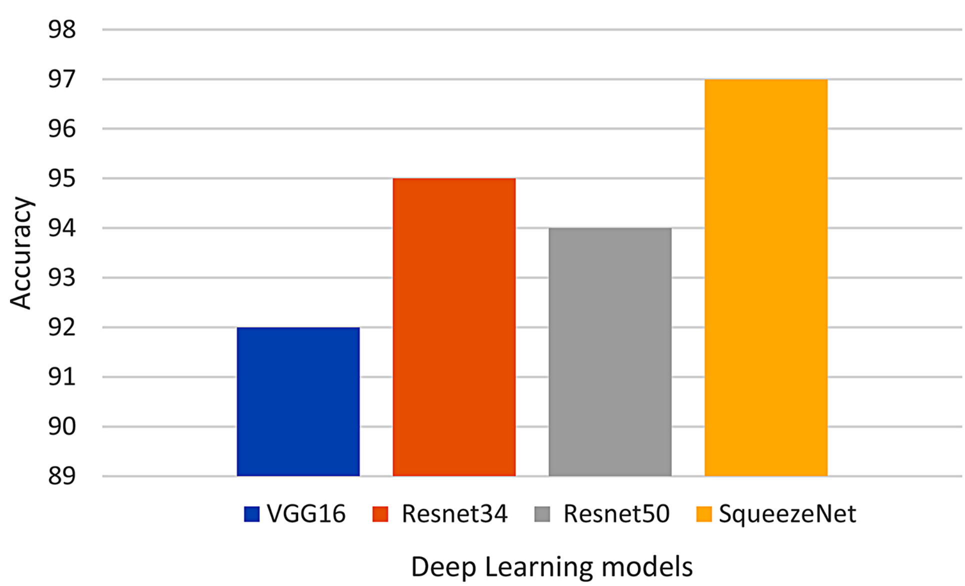

Fig. 10 Accuracy scores of deep learning models

Table 5 Error scores of models

	VGG	Resnet34	Resnet50	SqueezeNet
MSE	0.28	0.16	0.17	**0.07**
RMSE	0.53	0.41	0.41	**0.27**
MAE	0.15	0.08	0.09	**0.04**

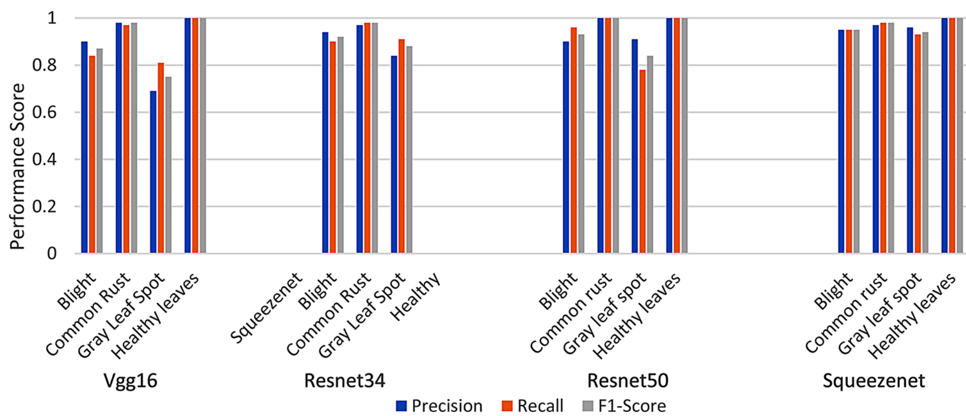

Fig. 11 Classification report

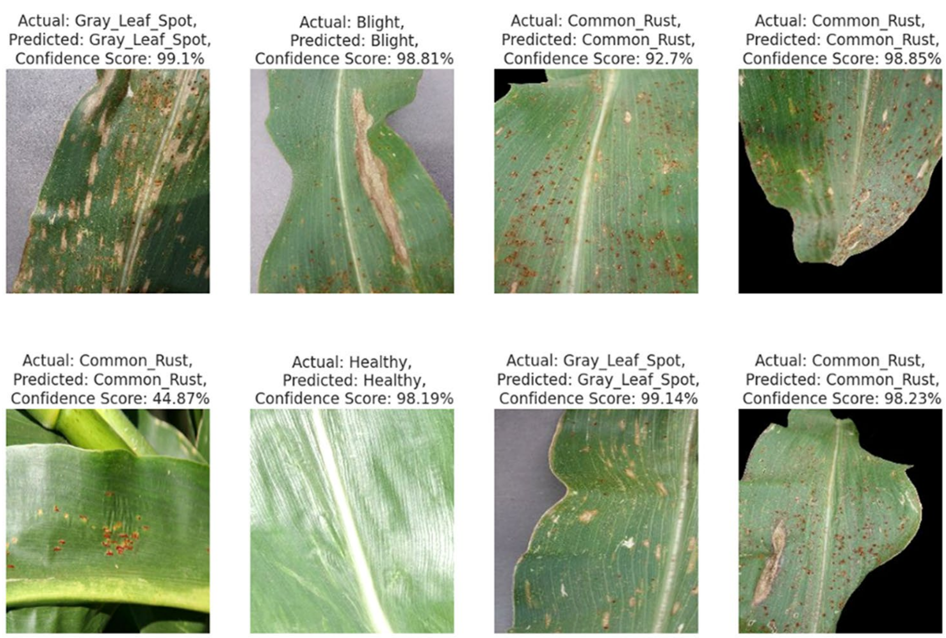

Fig. 12 Maize leaf disease prediction confidence score

4–11% reduced mean absolute error compared to VGG16, Resnet34, and Resnet50 deep learning models.

The classification report of maize leaf disease prediction using the proposed SqueezeNet model in comparison with other deep learning models such as VGG16, Resnet34, and Resnet50 are depicted in Fig. 11. The confidence score of maize leaf disease prediction using the proposed SqueezeNet model has been depicted in Fig. 12.

The results of the proposed work from Figs. 10 and 11; Table 5 clearly show that the proposed SqueezeNet model-based prediction preciously predicts the prediction of blight, common rust, grey leaf spot and healthy leaves with an accuracy of 0.97. Table 6 demonstrates that SqueezeNet outperforms the other models in terms of accuracy, recall, precision, and F1-score with reduced mean square error, which indicates improved performance in identifying and classifying maize leaf images.

Table 6 Comparison of the results with existing State of the Art (SOTA) models

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	MSE (%)
VGG16	92	90	93	91	0.28
Resnet34	93	91	94	92	0.16
Resnet50	94	92	95	93	0.17
SqueezeNet	97	95	98	96	0.07

Conclusion

The identification and classification of images of maize leaves using several deep-learning models have been addressed in this article. The proposed approach was evaluated using information from the Plantvillages dataset, which includes 3852 images divided into four classes: rust, spot, healthy, and blight. The dataset has been pre-processed with sampling and image labelling. The SMOTE algorithm maintains the balanced class and avoids overfitting problems. This dataset has been trained, validated, and tested by various deep learning algorithms, namely, VGG16, Resnet34, Resnet50, and SqueezeNet. Performances of these deep learning models are evaluated with metrics such as accuracy, recall, precision, F1-score, and confusion matrix. The SqueezeNet learning model produces an accuracy of 97% in classifying four different classes of plant leaf datasets, which has improved by 2-5% accuracy and reduced 4-1% of mean square error over VGG16, Resnet34, and Resnet50 deep learning models.

Author contributions

Prasannavenkatesan Theerthagiri: Conceptualization, Methodology, Software. A.Usha Ruby: Validation, Writing- Reviewing and Editing. J George Chellin Chandran: Data curation, Writing- Original draft preparation, Tanvir Habib Sardar: Writing- Original draft preparation. Ahamed shafeeq B M: Writing- Reviewing and Editing , Revision draft preparation.

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Data availability

Data available on request from the authors.

Declarations

Ethical and informed consent for data

Nil.

Conflict of interest

The authors declare no conflict of interest.

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