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Research paper

DeepDetectCorn: Transfer Learning-Powered Deep Learning for Corn Crop Disease Recognition

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Abstract

Plant diseases and pests are the main variables affecting corn output and quality in agriculture. Identifying corn leaf diseases is challenging for farmers worldwide, hindering effective prevention efforts. Using manual methods to diagnose corn infections can be time-consuming, subjective, and difficult. This investigation employs various convolutional neural network (CNN) models to identify three corn diseases and healthy leaves through classification techniques, feature extraction, and image enhancement. Preprocessing using data augmentation expanded datasets and reduced overfitting. CNN layers automatically retrieve features. The dataset contains images in four different categories. Three of them are disease-related, and one is about healthy leaves. Common rust, blight, and gray leaf spot are the diseases taken into consideration. The dataset includes 4,188 corn leaf images. To verify, CNN models (CNN, VGG19, Xception, ResNet-152, EfficientNetV2L, and InceptionResNetV2) were implemented and compared. The EfficientNetV2L and Xception models performed well with 99.37% and 99.15% test accuracy. The performance of the other models is also noteworthy. The study confirmed that the CNN algorithms can be a suitable option in identifying corn leaf diseases.

Keywords: *Convolution Neural Networks; Corn Crop Diseases; Deep Learning; Transfer Learning; Machine Learning.*

1. Introduction

The agriculture industry is a cornerstone of many nations' economies. The profitability of agricultural output is crucial for both established and developing economies. This industry provides jobs in rural areas, provides oxygen, aids food production, and has medical and industrial applications [1].

Farmers face numerous challenges in managing weather and other environmental factors that influence crops. Farming systems must manage plant diseases, which is a big threat. It adversely impacts plant development, production quality, quantity, and economic loss [2].

Corn is a widely used spice. Corn, or maize, is a tall, sturdy grass that produces cereal grain. About 9,000 years ago, southern Mexican farmers cultivated corn from wild teosinte. Corn is a frequently farmed crop. This cereal grain is highly nutritious and popular globally, known for its quick growth and adaptability to different weather. Corns are susceptible to diseases caused by nonbiological factors, negative environmental conditions, and other factors. Farmers have severe economic repercussions due to decreased production yield and quality. There are many diseases that damage the corn roots, leaves, and stems. Due to their perfect environment, leaves are best for illness diagnosis [3]. The symptoms of corn diseases, which affect leaf size, shape, and color, are visible on corn leaves [4].

Plant infections (bacteria, fungus, and viral diseases), microelement shortages, pests, and sucking insect pests create leaf patches [5]. Corn infections are assessed visually by farmers and professionals using naked eye inspection. This procedure is arduous, inefficient, expensive, and poor for disease detection [6]. Researchers also tried to diagnose diseases chemically; however, they involve substantial testing and are not real-time [7]. Erroneous disease identification increases pesticide use and residue levels, which lowers agricultural production. Farmers must prioritize early illness detection, fast response, timely diagnosis and detection, and infection prevention to reduce losses and increase profits.

An effective and precise plant disease recognition model is needed to overcome the limitations. Researchers are using computer algorithms to monitor large agricultural fields and identify sickness symptoms to create a reliable, farmer-friendly recognition system. Accurate and fast computer-based diagnostic algorithms for corn diseases are essential for effective and reliable disease detection. Use of technologies such as artificial intelligence, computer vision, machine learning, and deep learning is now very vital for corn disease detection, classification, and treatment suggestions. Agriculture has also adopted computer vision-based intelligent systems to promote efficiency and productivity [8].

Recently, improved machine learning and deep learning algorithms have been used for recognition and classification across many fields. Deep learning, a new machine learning field, is very popular for plant disease detection. Analyzing and interpreting composite input data, such as feature extraction and categorization, can yield significant results and enhance efficiency. Convolutional neural networks are among the most effective deep learning algorithms for image recognition in the field of deep learning.

Deep learning automatically retrieves crucial information from the input image during learning, which is its main benefit above standard machine learning [9]. CNN achieves good classification accuracy despite reducing manual engineering [10]. CNN excels at corn illness diagnosis, general image categorization, leaf classification [11], and flower recognition [12]. We found that deep convolutional neural networks outperform established methods in plant disease recognition [9]. The investigators also found that deep learning classified normal and diseased cells better than previous machine learning methods [13].

There is a high demand for accurate, cost-effective, and speedy corn disease diagnostics, yet the agriculture sector and farmers struggle with this. This paper uses a corn leaf disease images dataset to identify corn illnesses and pests using powerful deep learning techniques. A curated leaf image dataset with three unhealthy leaf categories— blight, common-rust, gray-spot-leaf, and a healthy leaf category—has helped develop a corn disease diagnosis system. This study used six different CNN architectures. Since the leaf is centrally positioned in the images and emphasizes sickness indicators, CNN can accurately diagnose illness without segmentation. The technology will help farmers discover diseases early and reduce expert and farmer stress. Early disease detection helps control corn illnesses.

The primary contributions of this study are as follows.

- Initially, we have collected images of corn crop leaves affected by three diseases as well as healthy images, sourced from the Plant Village dataset.
- Secondly, we developed and trained the six proposed models using our acquired dataset.
- The models demonstrated substantial efficacy in categorizing images of corn crops, even amidst diverse and intricate backdrops.

This paper commences with an introduction; the subsequent sections are organized as follows: Section 2 discusses various related research work, Section 3 delineated the methodology with materials and, the experimental setting. Sections 4 and 5 address the results and a discussion, respectively. The work is concluded in Section 6.

2. Related work

Using deep learning techniques, several researchers worldwide are doing tests to identify diseases of corn crops in digital images. Mohanty et al. [15] used deep learning techniques to diagnose 26 illnesses in 14 different crops. They utilized the publicly accessible "PlantVillage" image dataset [35], which has over 50,000 images of various crops, including potatoes, corn, cherries, apples, and tomatoes. For their experiment, they used GoogleNet [17] and AlexNet [16] with transfer learning in their work.

Several recent studies have explored the application of deep learning models for the detection and classification of corn leaf diseases, aiming to enhance food security and support sustainable agriculture in developing regions. Maria Tariq et al. [18] implemented the VGG16 model to classify corn leaves into four categories: Healthy (H), Blight (B), Gray Spot (GS), and Common Rust (CR). This model facilitated early disease detection and classification, contributing to improved crop management and economic stability. Additionally, the study integrated Layer-wise Relevance Propagation (LRP) for explainable AI, thereby increasing the model's reliability and interpretability. Chunguang Bi et al. [19] modified the MobileNetV3 architecture with cross-layer connections and dilated convolutions, resulting in an accuracy of 98.23% on a hybrid corn leaf disease dataset. Daneshwari Ashok Noola et al. [20] proposed an enhanced K-Nearest Neighbors (KNN) model incorporating advanced mathematical modeling and an optimized Directional Set strategy, achieving 99.86% accuracy in early disease classification. Kazi Tanvir et al. [21] developed DenseViT, a vision transformer-based model trained on 4,354 maize leaf images across four disease classes, achieving an accuracy of 98.85%. Fathimathul Rajeena et al. [22] introduced an EfficientNet-based model for corn disease detection, achieving 98.85% accuracy while maintaining computational efficiency. Rubina Rashid et al. [23] presented the Multi-Model Fusion Network (MMF-Net), integrating multiple classifier streams through RL-block and PL-block mechanisms, achieving up to 99.23% classification effectiveness. Shixiong Yang et al. [24] utilized YOLOv8 with Slim-neck and Global Attention Mechanism (GAM) modules for field-based corn leaf disease detection, achieving a precision of 95.18% and average accuracy of 94.65%. Ping Dong et al. [25] adopted YOLOv5s-C3CBAM integrated with attention mechanisms and CycleGAN-generated synthetic data, achieving an average precision of 83%. Qinru Ni et al. [26] developed a classification model using the VIP algorithm and Random Forest (RF), where a VIP-KNN variant achieved 97.46% accuracy. Yanxin Hu et al. [27] proposed a lightweight corn disease detection model based on YOLOv5s improvements, enhancing accuracy without increasing model size. Faiza Khan et al. [28] demonstrated a deep learning-based maize disease classification approach using a dataset comprising Blight, Sugarcane Mosaic Virus, and Leaf Spot, achieving accuracy rates ranging from 69.40% to 99.04%. In 2024, Theerthagiri et al. [29] introduced a Deep SqueezeNet model for maize leaf disease diagnosis, achieving high accuracy with reduced computational complexity. Mohanty et al. [30] conducted a field study in Bangladesh employing advanced deep learning models like ResNet50GAP and DenseNet121, achieving up to 99.65% accuracy in corn leaf disease classification. Vimalkumar and Latha [31] proposed a Manta-Ray Foraging Optimization with Deep Learning model for maize leaf disease detection, demonstrating superior accuracy. Fadhilla et al. [32] implemented a Convolutional Neural Network (CNN)-based model to recognize corn leaf diseases, demonstrating promising classification performance on localized datasets. Their approach focused on automated visual recognition, which is crucial for non-expert end users in agricultural settings. Hansamali Paula et al. [33] developed a mobile application powered by a pre-trained VGG16 CNN architecture to detect major maize leaf diseases, including northern corn leaf blight, common rust, and gray leaf spot. The application achieved a testing accuracy of 93%, highlighting its practicality for real-time disease detection in resource-limited regions. Masood et al. [34] introduced MaizeNet, a custom deep learning architecture tailored for maize leaf disease classification. Their model, evaluated using extensive experimentation, outperformed several standard architectures and achieved superior recognition accuracy, thus establishing MaizeNet as a scalable solution for agricultural disease monitoring.

3. Methodology

Figure 1 illustrates the comprehensive process of the proposed corn disease recognition methodology utilizing different CNN architectures. Initially, we acquired and stored images of corn crops from PlantVillage dataset. Subsequently, various image augmentation and processing methods were applied to these corn images. Subsequently, the corn images obtained are divided into two categories: testing and training

sets. Following that, we trained all introduced models using the training set obtained. Upon finishing model training, all models were also trained using the test set based on their performance. Finally, the best model was selected for the corn leaf disease identification.
Grounded in their proven efficacy in image classification and feature extraction tasks, especially in agricultural and medical imaging domains, CNN-based architectures, including Basic CNN, VGG19, Xception, ResNet-152, EfficientNetV2L, and InceptionResNetV2, are chosen for corn crop disease detection. A basic CNN provides a benchmark for performance and helps one to grasp baseline skills in pattern recognition of diseases. VGG19 is efficient at differentiating minor variations in leaf textures and colors produced by different diseases since its deep and homogeneous structure fits for learning hierarchical characteristics. Based on depthwise separable convolutions, Xception presents a potent and effective architecture to capture spatial correlations in images with reduced computational cost. ResNet-152, a very deep network with residual connections, solves the vanishing gradient issue and helps the model to learn more intricate characteristics from big and varied datasets. Ideal for obtaining high accuracy while keeping computing economy, EfficientNetV2L increases depth, width, and resolution in a compound manner based on its known optimal performance-to-parameter ratio. Finally, InceptionResNetV2 allows rich multi-scale feature learning necessary for the detection of several stages and types of corn crop diseases by combining the representational capability of inception modules with the training benefits of residual connections. These models' different architectural strengths make them together strong for the precise and effective detection of corn crop diseases.

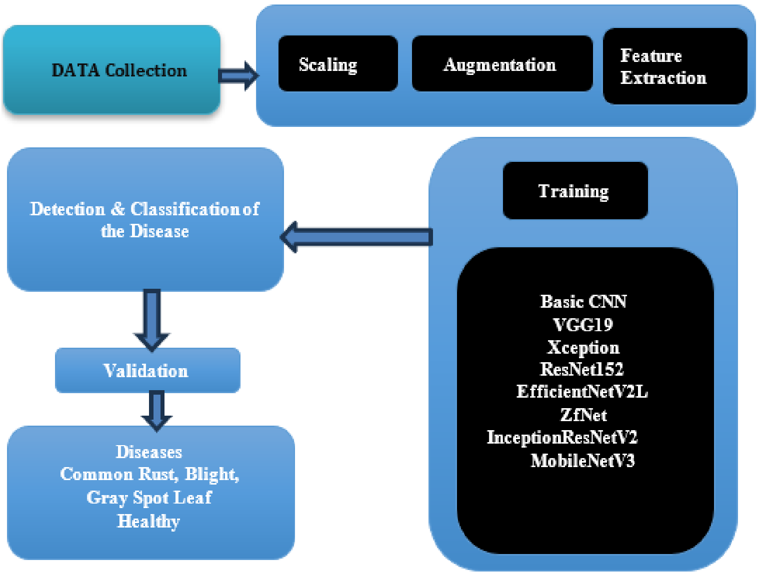

Fig. 1: Proposed Methodology.

The process begins with data collection, where images of plant leaves are gathered for analysis. Once collected, the data undergoes preprocessing, which involves three key steps: scaling to normalize the image sizes or pixel values, augmentation to artificially expand the dataset through transformations (such as rotation, flipping, etc.), and feature extraction to identify and isolate relevant patterns or attributes from the images. After preprocessing, the data is used for training various deep learning models, including Basic CNN, VGG19, Xception, ResNet152, EfficientNetV2L, ZfNet, InceptionResNetV2, and MobileNetV3. These models learn to identify disease-related features through iterative learning. Following training, the models are used for the detection and classification of plant diseases, where each input image is analyzed and classified into a specific category. The results are then subjected to a validation phase to ensure the accuracy and reliability of the classification. Finally, the system categorizes the plant leaves into one of the following outcomes: common rust, blight, gray leaf spot, or healthy, providing actionable insights for further agricultural intervention.

3.1. Dataset

The availability of superior and varied datasets is essential for advancing the agricultural sector. These datasets give the essential groundwork for the development of robust machine learning models and detection systems. This study selected the PlantVillage dataset [35]. The PlantVillage dataset is renowned for its comprehensive compilation of labeled images, encompassing various plant species and disease categories, rendering it an asset for model training. A total of 4,188 images were collected from the PlantVillage dataset and utilized in this research. Table 1 gives the details of the dataset. Illustrative images from the datasets are presented in Figure 2. These datasets offered essential knowledge and insights applicable to our goal. The datasets were divided into an eighty percent training set and a 20 percent test set utilizing the stratified shuffle split approach to ensure rigorous training and evaluation. This partitioning approach maintains the distribution of samples among various classes, therefore maintaining the dataset's integrity. For our experiments, we have selected the images of the leaves having diseases like blight, common rust, gray leaf spot, and healthy.

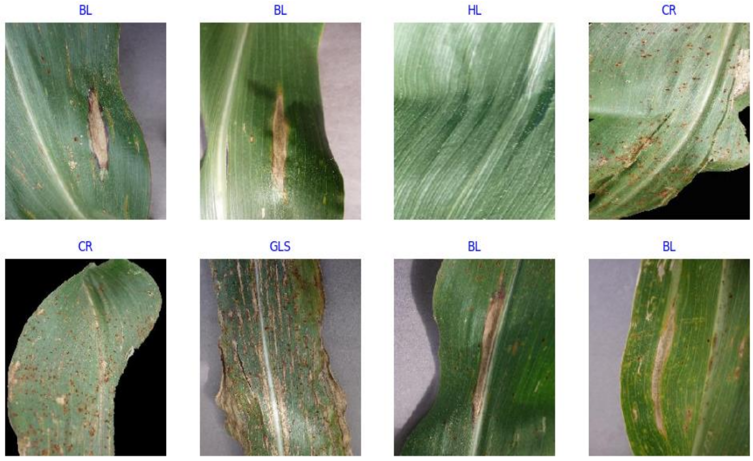

Fig. 2: Sample Images (BL=Blight, CR=Common Rust, GLS-Gray_Leaf_Spot, and HL=Healthy).

Table 1: Corn Leaf Disease Prediction Dataset Findings

Corn Leaf Diseases	Total Images
Gray leaf spot (GLS)	575
Common rust (CR)	1306
Blight (BL)	1145
Healthy (HL)	1162

3.2. Data preprocessing

Data preprocessing is performed to improve the quality of the images in the dataset used. Data preprocessing is also done to ensure data balancing across every class for accurate classification. Contrast-limited adaptive histogram equalization (CLAHE) technique is used in this work to improve contrast in all corn leaf images, which in turn improves image quality, detection, and classification across various difficult levels [36]. The initial step involves dividing the corn leaf images into smaller segments through nominal separation, followed by the application of histogram equalization to each segment. Equalizing the image's grey value highlights the hidden shape-related information. The image's sharp edges are safeguarded by defined boundaries within a specified area, and a grey spectrum is employed to represent the image. CLAHE limits amplification at a level indicated by a clipping histogram. Equation (1) uses the Rayleigh distribution for the clipping histogram.

$$P = P_{min}\left[2(\alpha^2)\ln\left(\frac{1}{1-d(F)}\right)\right]^{0.5} \quad (1)$$

In this context, P_{min} and P denote the minimum and measured values of a pixel, respectively. The parameter α signifies the threshold (clip parameter), while $d(F)$ represents the distribution function. The improved corn leaf images undergo processing in the next stage of data augmentation, which seeks to achieve a balance between the two datasets.

3.3. Deep learning models

Deep learning relies on the availability of large datasets for training and the computational capability of advanced processing units. Consequently, various deep learning architectures have arisen, varied in aspects such as complexity, scalability, efficiency, and optimization. This study utilized six models, comprising: CNN, EfficientNetV2L, InceptionResNetV2, ResNet152, Xception, and VGG19.

A fundamental architecture in deep learning, convolutional neural networks (CNNs) are especially suited for image processing chores. Layers include convolutional layers, pooling layers, and fully connected layers, which are meant to extract hierarchical spatial information from input data [38] make up a CNN. While pooling layers cut spatial dimensions and computational expense, convolutional layers use learnable filters to identify characteristics, including edges and textures. Convolutional filters' weight-sharing method helps to lower overfitting and reduce parameters. End-to-end trainable and able to learn intricate characteristics via backpropagation are CNNs. Originally presented in LeNet-5. CNNs became somewhat well-known after AlexNet performed on ImageNet. Modern CNNs find extensive usage in medical imaging, object detection, and image classification. For visual recognition activities, they offer scalability and a great degree of precision. CNN's popularity has motivated the creation of even more intricate designs, including ResNet and EfficientNet.

Proposed by Tan and Le (2021) [39] as an enhancement on the original EfficientNet models, EfficientNetV2L is a component of the EfficientNet V2 family. The "L" variation is a big model designed for efficiency and accuracy. To increase training speed and generalizing ability, EfficientNetV2L combines depthwise separable convolutions with Fused-MBConv blocks and progressive learning techniques. The model presents compound scaling to concurrently maximize network depth, width, and resolution. EfficientNetV2L trains far quicker than previous models and achieves state-of-the-art accuracy on ImageNet. Its design also considers hardware resource availability and real-world limitations, including latency. Industrial and academic research for uses needing great performance has embraced EfficientNetV2L extensively. Its pre-trained weights and modular design help it to be fit for transfer learning. The architecture follows a more general trend toward effective deep learning under computing restrictions.

Introduced by the Visual Geometry Group of the University of Oxford [40], VGG19 is a deep convolutional neural network architecture [40]. Using tiny 3x3 convolutional kernels throughout, it comprises 19 weight layers—16 convolutional layers and 3 fully connected layers. The architecture uses ReLU activations after each convolution and is distinguished by its simplicity—a repeated stack of convolutional layers followed by max-pooling. The network stresses depth as a technique of raising Imagenet dataset's high accuracy and increasing classification performance. VGG19 is computationally costly in terms of both training time and inference memory, even with its success. It lacks architectural innovation like skip connections, which makes training deeper versions more challenging. Still, VGG19 is extensively

employed in transfer learning as a feature extractor. It has been applied extensively in picture segmentation, object detection, and style transfer as well as in the simple form of the model makes it an interesting baseline for architectural research.
ResNet-152 is a very deep residual network expanding the ResNet architecture to 152 layers [41]. The approach provides identity shortcut connections that avoid one or more layers, therefore facilitating efficient training of quite deep networks. These leftover connections let gradients flow straight across the network, therefore reducing the vanishing gradient problem. ResNet-152 lowers computational cost by means of bottleneck residual blocks—a 1x1, 3x3, and another 1x1 convolution. It won the ILSVRC 2015 contest and performed first on the ImageNet categorization challenge. With depth, the model scales efficiently and provides better performance than shallower equivalents as ResNet-50 and ResNet-101. Still, it comes at the expense of more memory use and training time. Semantic segmentation, object detection, and image recognition are just a few of the vision tasks where ResNet-152 finds extensive use. Many later architectures that follow residual learning ideas clearly show their impact.
François Chollet [42] first presented Xception in 2017, a variation on the Inception architecture using depthwise separable. Reducing computing complexity and enhancing performance results from these convolutions decoupling of the learning of spatial and channel-wise data. Xception substitutes linear stacks of depthwise separable convolutions joined with residual connections for conventional Inception modules. This design lowers the parameter count yet improves the generalizing capacity of the model. Xception beats InceptionV3 on common benchmarks like ImageNet even with a same parameter budget. It shows that, with suitable design, simpler, factorized architectures can produce state-of- the-art results. In situations calling for great efficiency, including mobile or embedded applications, the paradigm is very successful. Xception is rather common in downstream computer vision projects and transfer learning. Its introduction marked a shift toward architectural minimalism and efficiency without sacrificing accuracy.
InceptionResNet V2 is a hybrid deep learning architecture that combines the Inception module with residual connections [43] [44]. The model integrates the multi-path convolutional operations of the Inception family with the residual identity mappings from ResNet, leading to improved convergence and performance. Starting ResNetV2 has over 50 million parameters and is one of the deepest and most accurate models in the Inception family. Its design features Inception blocks (A, B, and C) interleaved with residual connections, enabling better gradient flow during training. It achieves competitive accuracy on ImageNet and performs well on a variety of transfer learning tasks. Despite its complexity, the model maintains efficient computation through dimensionality reduction and parallelism. InceptionResNetV2 is frequently used in research and production, especially in applications requiring fine-grained image classification. Its architecture demonstrates that hybridization of successful design paradigms can yield state-of-the-art models. The model continues to serve as a robust backbone in computer vision pipelines.
We have also used a transfer learning approach in our research. Transfer learning in deep learning denotes the application of acquired knowledge to a novel task. In this, deep learning or machine learning models are trained and evaluated on an image dataset, then their assigned weights are used to train and infer on another image dataset. Transfer learning's main benefit is reducing model training time. [45]. Consequently, our study employed six deep CNN models described above, which were trained on the ImageNet dataset [46], and their pre-trained weights are accessible within the TensorFlow framework.

4. Results

The proposed models have been tested using the collected corn plant leaf images. we employed various deep learning models to detect and classify diseased and healthy leaves. A rigorous set of assessment criteria was used to completely assess the performance of the proposed deep learning models. Apart from this, our work used conventional deep learning architectures, choosing Adam optimizer and categorical cross-entropy as the loss function, both of which are generally acknowledged for their efficiency in multi-class classification problems. Table 2 gives the details of the parameters used.
Simulations on the corn image dataset (Plant Village) were carried out to illustrate the performance of the suggested deep learning systems and to compare their results. On a Windows 11 desktop with an Intel i7 11^{th} generation CPU and 16GB of RAM, the TensorFlow Keras program for the presented work was implemented and tested. Training and testing sets were separated using a ratio of 80 to 20%. The training set contained 4188 images divided into four classes.

Table 2: Training Parameters

Parameters	Values
Image Size	150 x 150
Batch Size	32
Epochs	40
Learning Rate	0.001
Loss Function	Categorical Crossentropy
Optimizer	Adam

The study evaluates five standard measures: Recall, Precision, Accuracy, Area under the curve (AUC), and F1-score, which are defined as follows.
Accuracy ensures the generation of suitable outcomes based on the provided leaf images. Precision assesses the performance of a classifier with a high level of detail. When the plant leaf exhibits low positive values, the precision is expected to be high. Conversely, when the corn plant leaf displays high positive values, the precision is anticipated to be low. Recall quantifies the completeness of the classifier's predictions. An increase in recall results in the detection of a greater number of positive samples. The F1-score is derived from the calculations of precision and recall. In this context, TN represents True Negative, FN denotes False Negative, TP indicates True Positive, and FP signifies False Positive.
The training loss is a statistic utilized to evaluate the fit of a deep learning model to the training data. In other words, it evaluates the model's error on the training dataset. The training set constitutes a segment of a dataset employed for the initial training of the model. The training loss is computed by summing the mistakes for each instance in the training dataset. Conversely, test (validation) loss is a statistic employed to evaluate the performance of a deep learning model on the test (validation) set. The test set is a segment of the dataset reserved for assessing the model's performance. The test (validation) loss closely resembles the training loss and is derived from the aggregate of mistakes for each instance in the validation set. The area under the ROC curve (AUC) signifies the likelihood that the model will opt for a randomly selected positive instance over a negative one. The AUC is an effective metric for evaluating the performance of two distinct models, provided that the dataset is approximately balanced. The model with a larger area under the curve is typically superior.

Table 3: Evaluation Measure details

Measure	Description	Formula
Accuracy	Proportion of correctly classified instances among the total instances.	Accuracy = (TN + TP) / (TN + FP + TP + FN)
Precision	Proportion of true positive predictions among all positive predictions.	Precision = TP / (TP + FP)
Recall	Proportion of true positive predictions among all actual positive instances.	Recall = TP / (TP + FN)
F1 Score	Harmonic mean of precision and recall, balancing between precision and recall.	F1 Score = (2 x Precision * Recall) / (Precision + Recall)

Table 4 presents a comparative analysis of the results achieved with six different deep learning models utilized for disease recognition in corn crop imagery. These results are obtained using a test dataset. The table presents the metric values acquired for the identification of corn crop diseases. The table indicates that the EfficientNetV2l model achieved the best results in terms of accuracy (99.37%), precision (95.83%), recall (95.17%), and F1 score (93.22%) metrics. The Xception model also achieved the best results for accuracy (99.15%) and AUC (99.71 %). In general, all models considered here have produced good results. In the same way, Table 5 presents the results achieved with the training dataset. The table indicates that the ResNet152 model achieved the best results in terms of accuracy (99.87%), precision (100%), recall (99.87%), and F1 score (99.81%) metrics. The Xception model achieved the best results for all metrics. In general, all models have produced good results.

Figure 3 shows the confusion matrices for all the models used in this research. Figure 4 shows the graphical representation of the results achieved for the evaluation measures. Figures 5 and 6 show the graphical comparison of all models used for corn crop disease detection and classification. Figure 7 shows a comparison of existing models in the literature for corn crop disease detection and classification.

Table 4: Evaluation Results Achieved for Evaluation Metrics with Test Dataset (CNN = CN, Xception = XC, Efficientnetv2l =EN, Inceptionresnetv2 = IRN, Resnet152 = RN, VGG19= VGN)

Metric	Models					
	CN (%)	XC (%)	EN (%)	IRN (%)	RN (%)	VGN (%)
Accuracy	85.52	99.15	99.37	88.28	93.79	91.72
Precision	85.52	95.17	95.83	90.14	93.79	92.31
Recall	85.52	95.17	95.17	88.28	93.79	91.03
AUC	98.25	99.71	99.28	98.97	98.79	99.03
F1_Score	69.29	92.94	93.22	77.14	90.21	87.84

Table 5: Evaluation Results Achieved for Evaluation Metrics with Train Dataset (CNN = CN, Xception = XC, Efficientnetv2l =EN, Inceptionresnetv2 = IRN, Resnet152 = RN, VGG19= VGN)

Metric	Models					
	CN (%)	XC (%)	EN (%)	IRN (%)	RN (%)	VGN (%)
Accuracy	84.35	99.48	99.22	95.60	99.87	97.67
Precision	85.54	99.48	99.22	97.65	100.00	98.31
Recall	82.66	99.48	99.22	91.33	99.87	97.54
AUC	97.70	99.99	99.89	99.69	100.00	99.96
F1_Score	73.62	99.33	99.03	93.72	99.81	96.76

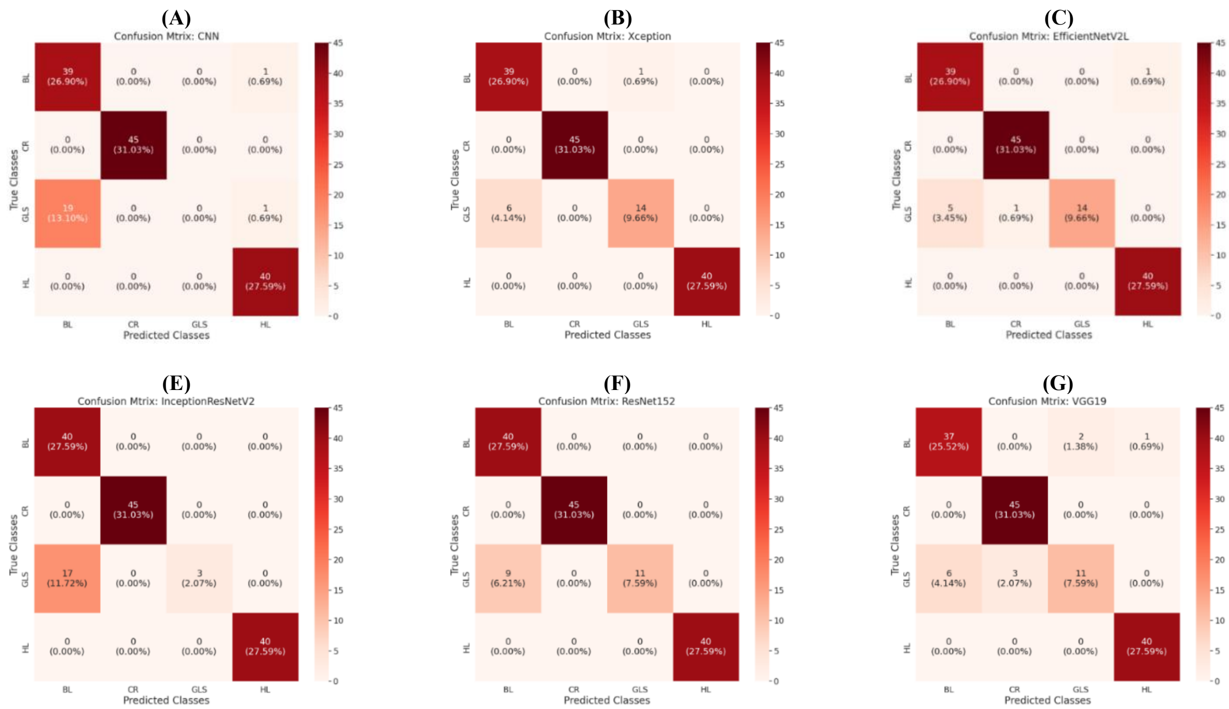

Fig. 3: Confusion Matrix: (A) CNN (B) Xception (C) Efficientnetv2l (D) Inceptionresnerv2 (E) Resnet152 (F) VGG19

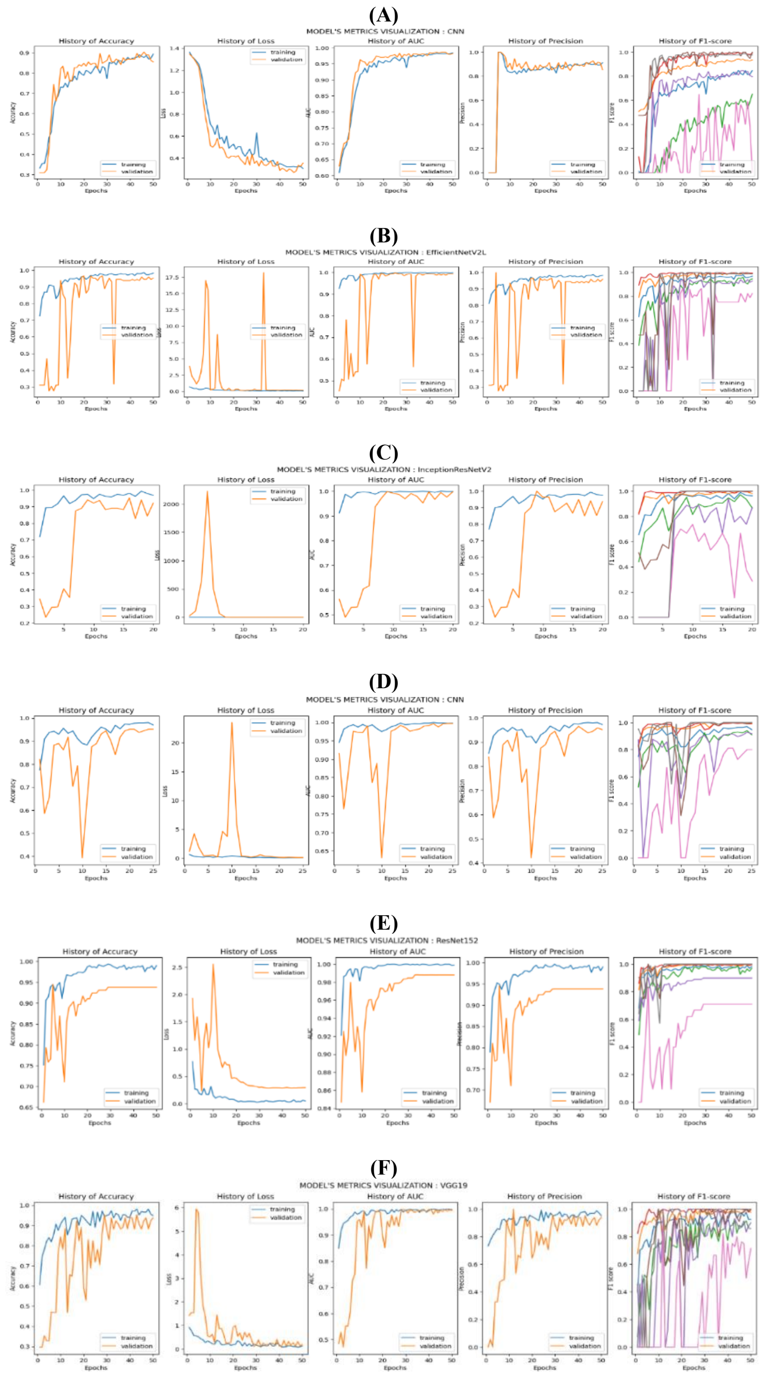

Fig. 4: Loss and Accuracy Graphs: (A) CNN (B) Efficientnetv2l (C) Inceptionresnetv2 (D) Xception (E) Resnet152 (F) VGG19.

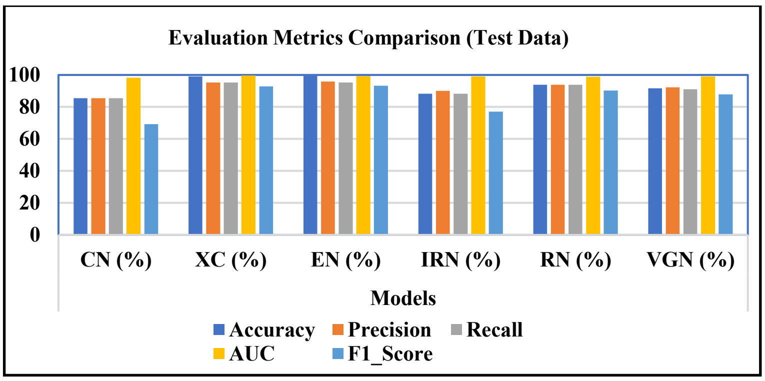

Fig. 5: Evaluation Metrics Comparison (Test Data).

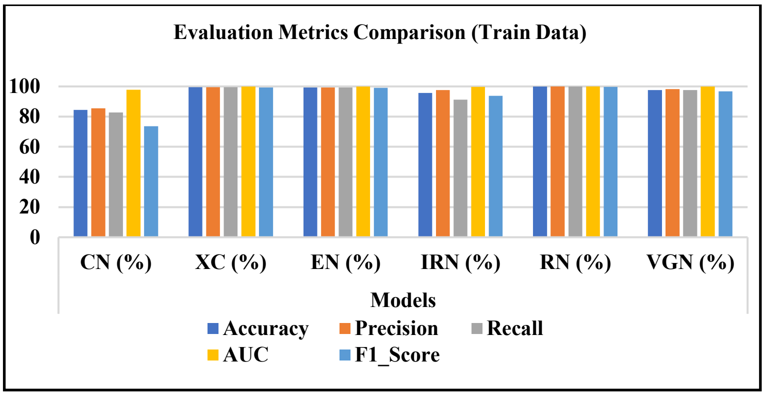

Fig. 6: Evaluation Metrics Comparison (Train Data).

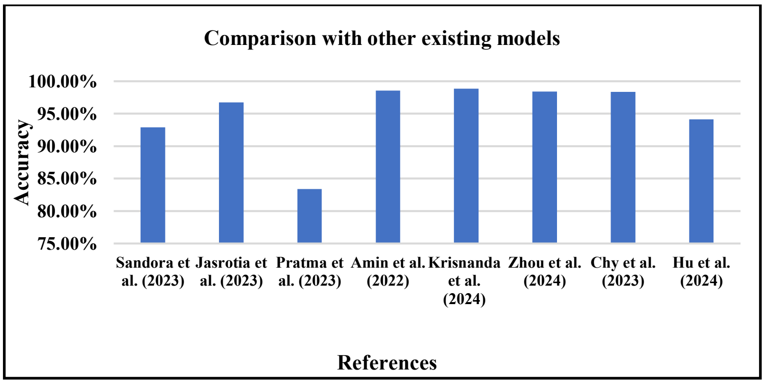

Fig. 7: Comparison with Other Existing Models.

5. Discussion

This research established six deep learning models: CNN, Xception, EfficientNetV2l, InceptionResnetV2, ResNet152, and VGG19. All models showed proficiency in identifying common rust, blight, gray leaf spot diseases, and healthy leaves in corn plants. The EfficientNetV2l model attained a test accuracy of 99.37%, whereas the CNN, Xception, InceptionResnetV2, ResNet152, and VGG19 models recorded average test accuracies of 85.52%, 99.15%, 88.28%, 93.79%, and 91.72%, respectively. The results indicate that all models can identify the presence of illnesses in corn plants. Moreover, these results are regarded as exemplary instances of an effective model, as an effective model is anticipated to achieve an accuracy of over 70% [55]. Nonetheless, deep learning models exhibit superior performance when trained on extensive datasets. The bulk of studies have utilized transfer learning to train deep learning models for the identification of corn diseases. A separate work by [20] created a deep learning model for the early identification of maize illness with a segmentation method, whereas our study employed a classification and detection strategy. Furthermore, when comparing the produced deep learning models, the EfficientNetV2l and Xception models exhibited superior accuracy relative to the other models. It effectively illustrated the performance of each layer and the parameters that may be adjusted to enhance accuracy, with five shared convolutional layers, max-pooling layers, dropout layers, three completely connected layers, a 7×7 filter size, and a reduced stride value in the initial layer. It uses deconvolution to visualize and comprehend convolutional networks. All models converged within a satisfactory timeframe, yielding favourable findings in this study. Table 6 presents a comparative analysis of the proposed method against existing models in the literature. The table indicates that the proposed approach achieved the highest recognition accuracy of 99.37% using a CNN-based deep learning model, which facilitates automatic feature extraction, whereas other methods attained lower accuracy.

Table 6: Comparison with Other Existing Models

Reference No.	Model Used	Accuracy (%)
Sandora et al. (2023) [47]	ResNet50, VGG19, EfficientNet-B0, InceptionV3,	92.91
Jasrotia et al. (2023) [48]	CNN	96.76
Pratma et al. (2023) [49]	AlexNet, LeNet, MobieNet	83.37
Amin et al. (2022) [50]	AlexNet, ResNet-50, SqueezeNet	97.56
Ahadian et al. (2024) [51]	EfficientNet-B0	97.87
Zhou et al. (2024) [52]	ShuffleNetV2	96.40
Chy et al. (2023) [53]	DenseNet201, CNN with dropout	97.36
Hu et al. (2024) [54]	LFMNet	94.12
Proposed	CNN, Xception, EfficientNetV2l, InceptionResnetV2, MobileNetV3, ResNet152, VGG19	99.37 (EfficientNetV2L)

Our work on deep convolutional neural network detection of corn leaf disease produced promising results. There are some areas, nevertheless, where more research could help enhance the robustness and accuracy of the model. One of the most crucial areas of future work will be growing the dataset used to train the model. The current 4188-image collection is limited in terms of image diversity and disease depiction. By gathering extra images, including more types of diseases and variations in leaf appearance, the deep learning system can be trained to identify a greater range of diseases. The models are presently trained to identify just three different diseases of corn leaves. Though many more diseases can damage corn leaves, it would be advisable to extend the detection capacity of the model to include a wider spectrum of diseases. Gathering additional images of different ailments and adjusting the model to identify them can help one achieve this. Investigating several neural network architectures will also be a focus of the next studies. This work made advantage of pre-trained architectures refined for our particular aim. For this work, other topologies, including graph neural networks or recurrent neural networks, could be more suited. Furthermore, we want to increase the diversity of the training set by means of GAN-based augmentation. Using generative adversarial networks (GANs), one can produce new images with varying leaf characteristics yet resembling the original dataset. This helps to prevent overfitting and increase the generalizing ability of the model toward fresh images.

Our research presented several challenges. One major challenge was insufficient computing capability. Deep convolutional neural networks—like those used in our work—need significant computational resources both for training and execution. The load included 4489 pictures in total. To control the volume of computational activities, we have to make use of strong hardware, including GPUs. Still, this remained difficult given the length of the training program and the significant computational resources needed. Finding the ideal hyperparameters for the model proved difficult and calls for much of trial and error. Developing a model that is user-friendly, easily available, and simple to use ultimately provided a major challenge. We made sure the models worked efficiently over a broad spectrum of devices and were easily navigable.

6. Conclusion

This investigation has demonstrated that it is feasible to detect corn diseases at an early stage, particularly concentrating on common rust, blight, and gray leaf spot diseases. A comprehensive dataset was assembled, consisting of 4188 images sourced from the Plant Village dataset. The open-source availability of the dataset will enhance the exploration of common rust, blight, and gray leaf spot diseases. Various deep learning models, including CNN, Xception, EfficientNetV2l, InceptionResnetV2, ResNet152, and VGG19, were created to tackle the challenge of early disease detection. All models were developed from the ground up, with EfficientNetV2l showcasing its capability to detect or classify disease, achieving a test accuracy of 99.37%. Following closely, Xception attained an accuracy of 95.15%. This underscores the significance of advanced learning models in the timely identification of plant diseases in corn. This study enhances agricultural technology and holds significant promise for farmers by promoting crop health and boosting yield. The current study examined deep learning techniques for identifying various corn leaf diseases. This method may effectively mitigate data scarcity and enhance the model's ability to generalize across various disease types and environmental factors. Ensemble models, including stacking and boosting, can enhance overall classification performance by integrating the unique insights obtained from each model.

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