Enhancing Maize Leaf Disease Detection using Transfer Learning Approach

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Abstract – *Maize is a staple food crop for many communities in India, especially in regions where it serves as a primary source of nutrition. It's consumed in various forms like cornmeal, popcorn, and as whole kernels. The agriculture sector is significantly important to India's economy. To stop crop loss and the spread of illness, early detection of plant diseases is essential. Farmers or plant pathologists will typically physically examine the plant leaf to determine the type of illness. Due of the various drawbacks of conventional inspection, scientists are focusing on implementing technology to streamline the procedure. To improve maize leaf disease detection precision, pre-trained models such as VGG16, VGG19, ResNet152 and EfficientNetB7 have been employed. The EfficientNetB7 model outperforms the others, with an accuracy rate of 98.56 %. This enhances crop productivity and guarantees the model's high degree of accuracy for illnesses of the maize leaf.*

***Key Words*: Agriculture, Artificial Intelligence, Deep Learning, Transfer Learning, Pre-Trained Models (PTMs), Visual Geometry Group (VGG)**

1. INTRODUCTION

In India maize is the third-most important cereal crop after wheat and rice[1]. Maize is extensively used as fodder for livestock such as poultry, cattle, and pigs. Its high nutritional content and digestibility make it a valuable component of animal feed. Maize is a versatile crop with numerous industrial applications. It's used in the production of cornstarch, corn syrup, ethanol, and other bio-fuels. Additionally, maize by-products like corn oil and corn gluten meal have various industrial uses [2]. Due to its many applications as food, feed, fodder, and raw materials for various industrial items, it is highly valued all over the world. Maize is very susceptible to a variety of plant diseases, despite its high nutritional value. Maize cultivation offers diversity to Indian agriculture, especially in regions where it's grown alongside other crops. Its resilience to various climatic conditions makes it an important crop choice for farmers, contributing to agricultural sustainability and resilience. Maize leaf diseases have a major effect on the amount and quality of products produced from maize. Diseases affecting maize cereals are influenced by soil type, temperature, and rainfall. It can be challenging to identify and categorize plant diseases in agriculture, even though they can be helpful in monitoring large agricultural fields and identifying disease symptoms as soon as they appear on plant leaves. The classification and detection of crop diseases are the most crucial technical and economical elements in the agricultural sector. For diseases of the maize leaf to be treated and controlled early detection is essential. There are numerous traditional techniques for classifying and identifying diseases in maize leaves, such as using chemicals, human operators, etc. However, there are a number of drawbacks to the traditional methods for identifying maize leaf diseases, including the fact that they are expensive, prone to error, time-consuming, inconsistent, and ineffectual. They also require specialized tools and plant disease knowledge. Feature representation and extraction are the two main limitations of machine learning. In current days, deep learning has greatly advanced the identification of plant diseases [3]. Convolution neural networks (CNNs) are widely employed for illness diagnosis in academia and industry [4]. Deep learning has come a long way in the previous several years. It can now extract useful feature representations from a vast array of input pictures. Deep learning broadens the application of computer vision in precision agriculture by enabling detectors to diagnose agricultural illnesses fast and correctly, in addition to improving plant protection precision. Numerous industries, such as those that make food and drink, poultry, and animal feed, require maize. A major component in the low maize production is the numerous infections that wreak havoc on the crop, drastically reducing its overall yield [5]. Consequently, farmers stand to benefit greatly from a device that can identify plant illnesses based on the appearance of the plant and its telltale symptoms. The development of disease in the host plant is favoured by low temperatures, cloudy conditions, and high humidity. Southern Corn Leaf Blight (SCLB) and Maydis Leaf Blight (MLB), is a fungal disease that affects maize and is caused by the plant pathogen. Bipolaris maydis, or Cochliobolus heterostrophus, as it is sometimes called Bipolaris Maydis (Nisikado) Shoemaker is the cause of Southern maize leaf blight (SCLB), also known as Maydis leaf blight (MLB), a fatal foliar disease that affects maize and has a wide geographic spread. Globally, producing regions developed in warm, humid environments. Early indications of the disease are little regions of necrosis that hover like haloes. The cause of southern rust is the fungus Puccinia polysora. Even though southern rust is usually thought of as a tropical illness, it can appear in areas of the United States and Canada that are important for maize production. There are typical rust-like signs, but the pustules are smaller and almost invariably located on the upper leaf surface. Spores appear orange when they come out of the pustule.

2. RELATED WORK

The integration of AI in maize leaf disease detection offers numerous benefits, ranging from early detection and accurate diagnosis to cost-effectiveness and sustainability. By transferring knowledge from these domains, the model can effectively learn relevant features for maize leaf disease detection with a smaller amount of annotated data. Pre-trained models have learned generic features that are broadly applicable across different image recognition tasks. By fine-tuning these models on maize leaf disease datasets, transfer learning enables the adaptation of these generic features to specific characteristics of maize leaves and diseases. This process often leads to better generalization performance, especially when faced with variations in imaging conditions, leaf morphology, or disease symptoms. A modest corpus of literature also discusses the different forms of maize illnesses. A three-step analysis method was developed by Chad DeChant et al.[6] to ascertain whether the pictures included diseased leaves. Matching predictions were aggregated into distinct heat maps, which were subsequently fed into a final CNN trained to identify if all of the images in the set contained infected plants. The three-stage architecture of this model is designed to improve performance. With a 96.7% accuracy rate, the system performs better than average. GoogLeNet and Cifar10, deep learning-based models for diagnosing leaf diseases, were proposed by Xihai Zhang et al. [7]. A collection of five hundred images, sourced from other places such as Google and Plant Village, depict various periods when diseases on maize leaves were common. At the top of the classification hierarchy, the GoogLeNet model can identify eight distinct types of maize leaf diseases with an average accuracy of 98.9%. Malusi Sibiya et al. [8] trained a CNN network to recognise and categorise maize leaf illnesses using Neuroph by using a smartphone camera, images of the diseases taken in several maize fields, and the Plant Village website. Three distinct types of maize leaf diseases were selected: common rust (Puccinia sorghi), northern corn leaf blight (Exserohilum), and grey leaf spot (Cercospora). Northern maize leaf blight (Exserohilum) was identified and classified by CNN with a high accuracy rate of 99.9%. An improved DenseNet architecture was proposed by Abdul Waheed et al. [9] for the purpose of discovering and classifying maize leaf diseases. They also trained four more popular CNN models for the detection and categorization of maize leaf disease, namely EfficientNet, XceptionNet, NASNet, and VGGNet. 12,332 photos in all, meticulously gathered from several sources, are categorized into 4 types of crops: the Cercospora-caused grey leaf spot (1644 images), common rust (3816 images), healthy crop (3720 images), and northern leaf blight (3152 images). With an accuracy percentage of 98.06%, the recommended DenseNet produced impressive results. Deep learning methods were suggested by Md. Ashraful Haque et al. [10] to detect maize crop disease. Deep learning has been suggested as a method for identifying images of a field-infected maize crop. Three major diseases Turcicum Leaf Blight, Maydis Leaf Blight sheath Blight, and Banded Leaf. Three different network configurations were simulated using the maize dataset. The results of the trial showed that the maximum accuracy of Inception-v3 GAP was 95.99%. A new CNN model named LeafNet was introduced in [11] to classify the tea leaf diseases and achieved higher accuracy than Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP)

In [12], two DL models named modified MobileNet and reduced MobileNet were introduced, and their accuracy was near to the VGG model; the reduced MobileNet actually got 98.34% classification accuracy and had a fewer number of parameters as compared to VGG which saves time in training the model. A state-of-the-art DL model was proposed in [13] named PlantdiseaseNet which was remarkably suitable for the complex environment of an agricultural field. In [14], five types of apple plant diseases were classified and detected by the state-of-the-art CNN model named VGG-inception architecture. It outclassed the performance of many DL architectures like AlexNet, GoogLeNet, several versions of ResNet, and VGG. It also presented inter object/class detection and activation visualization; it was also mentioned for its clear vision of diseases in the plants.

3. DATASET

Five groups of images—Northern maize leaf blight, Common rust, Southern rust, Grey Leaf Spot, and Healthy leaf—were selected from the Plant Village Dataset as shown in Fig1.

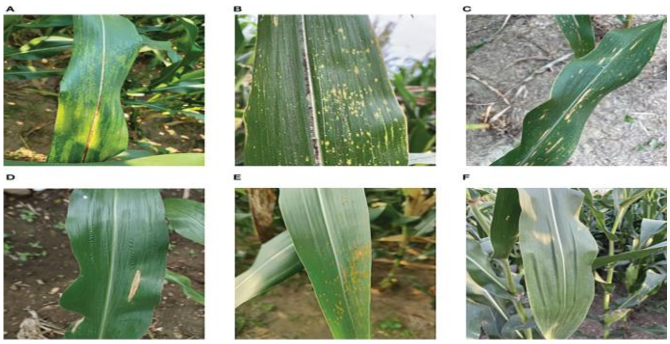


Fig 1: Few images from the dataset

3810 photos total from the collection are included, with the names of the diseases represented by five classes. The dataset includes 900 healthy photos, 760 images with common rust damage, 700 images with grey leaf damage, 650 images with Southern rust damage, and 800 images with Northern maize leaf blight damage. Deep learning models require a large dataset in order to function well. Using Keras' Image data generator, the images are resized to 224 x 224 pixel sizes, after which modifications like rotation, zoom, and shift are made.

4. PROPOSED METHODOLOGY

This section presents the data and main classifier models used in this investigation. Google Colab has been used in the implementation of the current study. Fig 2 displays the classification model's working diagram. This research uses an alternative way to categorize illnesses of maize leaves. After pre-processing, the process of obtaining features from the ones that already exist is known as feature extraction. Next, the dataset is appropriate for classification.

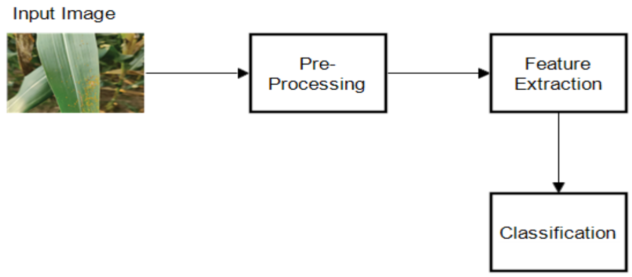


Fig 2: Methodology

This section explains the methods used to extract the most information from images of maize leaves. Among the methods employed are picture segmentation, image scaling, and colour space conversion. All of the photos in the collection have been reduced in size to 224 by 224 pixels. Their colour spaces are then converted to HSV for further processing. In the HSV colour space (Value), hue, saturation, and brightness levels of colour are all represented by three distinct terms [15]. An improved version of the Inception architecture, known as Inception-v3, has fewer parameters and good computing efficiency while scaling up. Since 2012, as the intricacy of the models employed in the ImageNet dataset has grown, so has success; yet, a large number of them remain computationally inefficient. The EfficientNetB7 model is a conglomeration of CNN models [16]. There are eight models in the EfficientNet group, and accuracy significantly outpaces growth in derived parameter numbers as the number of models rises. Unlike previous CNN models, EfficientNet replaces the Rectifier Linear Unit (ReLU) activation function with the Swish activation function. Deep learning architectures aim to increase the visibility of smaller, more efficient models [17]. The primary component of EfficientNet; yet, because of its larger FLOPS (floating point operations per second) budget, it is utilized somewhat more than MobileNetV2 [20]. Detailed discrete convolutions are used in this design, which almost doubles calculation efficiency over standard layers [18]. The kernel size controls the dimensions of the 2D convolution window. Initially, the images are reduced to 256 x 256 pixels for shallow networks, 224 x 224 pixels for VGG16 and VGG19, and 299 x 299 pixels for early networks. We do the model optimization and prediction on these rescaled images. Secondly, all pixel values are split by 255 to make them consistent with the baseline values of the network. Sample normalization is the third stage. Normalization facilitates more efficient end-to-end training. Transfer learning in maize leaf disease detection enhances data efficiency, generalization performance, convergence speed, and adaptability while conserving computational resources. By leveraging knowledge from related domains, transfer learning contributes to the development of more accurate, robust, and scalable AI-based solutions for managing maize diseases and ensuring global food security.

5. PRE-TRAINED MODELS (PTMs)

Pre-trained models are deep learning models that have been trained on large datasets for general tasks such as image recognition, natural language processing, or other machine learning tasks. These models have learned to extract features and patterns from data through the process of training on massive amounts of labeled or unlabeled data.

5.1. Visual Geometry Group 16 (VGG 16)

VGG16 is a convolutional neural network architecture that gained prominence for its simplicity and effectiveness in image classification tasks [19]. Developed by the Visual Geometry Group at the University of Oxford, VGG16 consists of 16 layers, including 13 convolutional layers and 3 fully connected layers as shown in Fig 3.

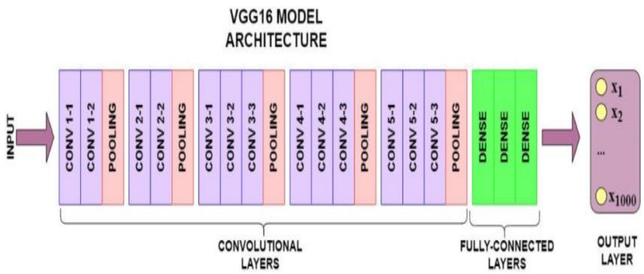


Fig 3: Architecture of VGG16

One of its key characteristics is the use of small (3x3) convolutional filters with a stride of 1 and max-pooling layers (2x2) with a stride of 2, which contributes to its uniform architecture. Despite its deep structure, VGG16 is relatively easy to understand and implement, making it a popular choice for researchers and practitioners in the field of computer vision. Although newer architectures have since surpassed its performance, VGG16 remains an essential benchmark and serves as a foundational model for understanding deep convolutional neural networks.

5.2. Visual Geometry Group 19 (VGG19)

VGG19 is a convolutional neural network architecture that builds upon the success of its predecessor, VGG16. Like VGG16, it was developed by the Visual Geometry Group at the University of Oxford. The '19' in its name refers to the total number of layers, which includes 16 convolutional layers and 3 fully connected layers. VGG19 maintains the simplicity and uniformity of architecture seen in VGG16, with small (3x3) convolutional filters and max-pooling layers (2x2).

5.3. Residual Network (ResNet152)

ResNet152 stands as a pinnacle in the realm of deep convolutional neural networks (CNNs), particularly renowned for its unprecedented depth and groundbreaking architectural innovation. Developed by researchers at Microsoft Research, ResNet152 introduced the concept of residual learning, which revolutionized how deep networks are trained. Fig 4 shows the architecture of ResNet152.

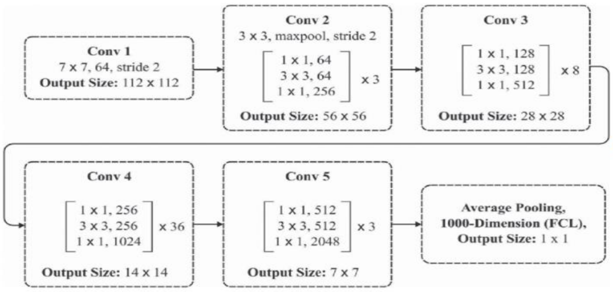


Fig 4: Architecture of ResNet152.

Residual learning addresses the vanishing gradient problem by introducing shortcut connections, or skip connections, that allow the network to bypass certain layers, effectively enabling the network to learn residual functions rather than directly learn the underlying mapping [21]. Its influence extends beyond performance benchmarks, shaping the landscape of deep learning research and inspiring subsequent architectural advancements.

5.4. EfficientNet

EfficientNetB7 represents a significant advancement in neural network design, characterized by its remarkable balance between model size and performance [22]. Developed by Google AI, EfficientNetB7 is part of the EfficientNet family, which leverages a novel compound scaling method to optimize model parameters for efficiency and effectiveness. This approach systematically scales the depth, width, and resolution of the network to achieve superior performance with fewer parameters, making EfficientNetB7 particularly well-suited for resource-constrained environments as shown in Fig 5.

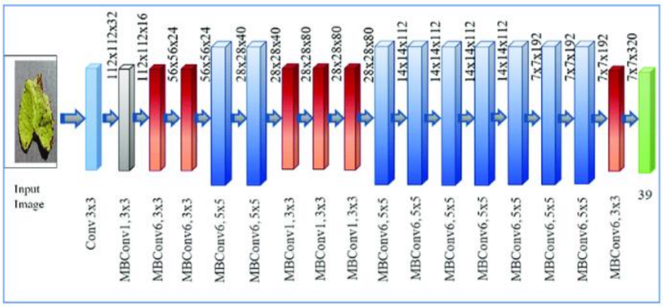


Fig 5: Architecture of EfficientNetB7.

Despite its efficiency, EfficientNetB7 exhibits impressive accuracy across various computer vision tasks, including image classification, object detection, and semantic segmentation. Its efficient architecture makes it highly deployable in real-world applications where computational resources are limited, while its powerful feature extraction capabilities ensure high performance. EfficientNetB7 stands as a testament to the importance of balancing model complexity and efficiency, setting a new standard for neural network design in the era of constrained computing resources.

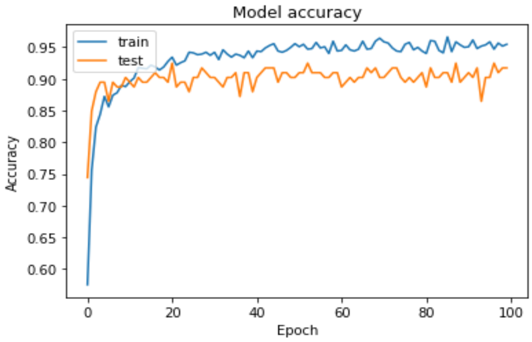
6. RESULTS AND DISCUSSION

Studies in the literature indicate that a useful method for classifying maize illnesses is to pre-train models using transfer learning. The experimental results are assessed using popular pre-trained models including VGG16, VGG19, ResNet152 and EfficientNetB7.

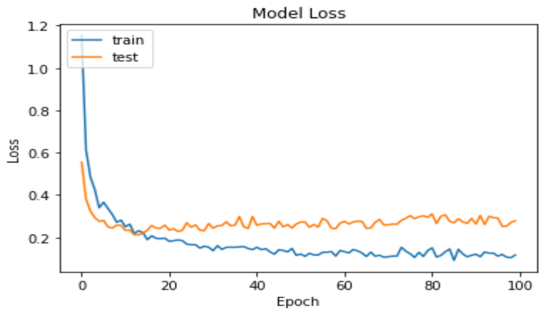
The 3810 picture dataset is divided in 80:20 ratio into training and testing sets in order to conduct the tests. The training set consists of 3000 photographs, while the testing set contains 810 photos. The image is resized to the resolution needed for the standard size required by the VGG16, VGG19, InceptionV3, and EfficientNetB7 models. The experimental results in Table I show that the VGG16 has a precision of 92.10 % and a classification accuracy of 92.10 %. In addition, VGG19 has outperformed VGG16 in accuracy with 94.17 % precision and 94.23 % accuracy. Moreover ResNet152 has an accuracy of 95.52 %. With an accuracy of 98.56 %, the EffectiveNetB7 model surpassed the other models as shown in Table 1. Further a high training accuracy was obtained from this model.

Table1: Results obtained from PTMs

Model	Classification Accuracy (CA)	Precision (P)	Recall (R)	F1-Score
VGG16	92.10	92.1	91.23	92.10
VGG19	94.23	94.17	93.10	94.2
ResNet152	95.52	95.43	94.32	95.5
EfficientNetB7	98.56	98.43	97.43	98.56



(a)



(b)

Fig 6: Curves (a) training accuracy (b) model loss

7. CONCLUSION

This work facilitates the early detection of maize leaf diseases, which is important in preventing crop loss and disease spread. A number of plant diseases are reliably predicted by the CNN model. Upon evaluating the efficacy of multiple pre-trained CNN models, such as VGG16, VGG19, ResNet152 and EfficientNetB7, the most accurate model is identified based on performance metrics. During testing, the model's performance evaluation criteria—precision, recall, accuracy, and F1 score—are applied. With an accuracy of 98.56%, the EfficientNetB7 model was the most accurate. AI-powered systems can detect maize leaf diseases at an early stage, even before they are visible to the naked eye. This early detection enables farmers to take preventive measures promptly, such as applying fungicides or adjusting agricultural practices, to mitigate the spread and impact of diseases. By accurately identifying and diagnosing diseases in maize plants, AI contributes to optimizing crop yields. Timely intervention based on AI-generated insights can prevent significant yield losses caused by diseases, ultimately ensuring food security and economic stability for farmers.

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