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Integrated Feature Fusion in Multiclass Maize Leaf Disease Recognition

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Abstract Plant diseases are the main factor in plant mortality and destruction, especially in trees. Early discovery, however, can assist to manage and treat this issue efficiently. To increase output, crop and plant lesions are detected and stopped as soon as feasible. Because it relies solely on visual observation, manual inspection of plant leaf diseases is time-consuming and expensive. The authors offer methods for identifying and categorizing plant leaf diseases using computer vision. Pre-processing original images to visualize contaminated areas, feature extraction from unprocessed or segmented images, feature fusion, feature selection, and classification are a few examples of computer vision approaches. The fusion technique is used to combine the target's numerical data features, which go beyond the picture, with the extracted image features to increase the target's feature representation. The following are the principal issues that researchers found in the literature: Low-contrast infected regions. Extract redundant and irrelevant information, which degrades classification accuracy; Redundant and irrelevant information may lengthen computation times and the targeted models performance will suffer as a result. This study proposed a framework for classifying plant leaf diseases based on the best feature selection and a deep learning fusion model. In the suggested approach, contrast is first enhanced using a pre-processing model, and then the issue of an unbalanced dataset is resolved via data augmentation. The proposed Deep Fusion Learning Model (DFLM) shows an accuracy of 98.8% in comparison with other models.

Keywords: Maize leaf, Classification, Deep Fusion learning model, Convolutional neural network.

1 Introduction

Over the past few years, the increase in plant diseases has had a substantial impact on the production of crops and the stability of our food supply. Thus, early disease detection is crucial for subsequent plant treatment and full-blown disease avoidance [1]. It also plays an important part in agricultural production management and decision-making. Plants with illness may exhibit visible stains or lesions on their leaves, flowers, or fruits. Each disease typically has a distinct visual pattern that can be used to identify plant problems. Plant leaves serve as the primary site for spotting disease signs, making them the predominant source for identifying plant health issues. [2]. Maize, also known as corn (Zea mays L.), is a cereal grain from the Gramineae/Poaceae family that has several uses, earning it the title "Queen of Cereals" [3]. It can be transformed into a range of products, including corn starch, corn-based foods and beverages, bio-ethanol, and more by grinding, alkali processing, boiling, heating, and fermentation. Due to its numerous industrial uses, this crop is particularly unique and distinct from its close relatives, rice and wheat. However, diseases in maize leave result in significant economic and production losses and reductions in the amount and quality of crop output.

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One of the primary variables influencing plant growth is the presence of plant diseases, and early diagnosis and accurate control of pests and diseases depend on the ability to detect and identify these diseases [4][5]. The food crop that is most widely grown is maize. Viruses and fungi-infected lesions are produced by diseased maize plants when they come into contact with them. Symptoms of the infection include deformation, curling, rotting, and discolourations in the affected leaf tissue. Identifying the disease species and locating plant disease hotspots quickly, easily, and accurately is essential. Determining plant diseases in their earliest stages is crucial because they significantly impact crop productivity [6]. Automatic detection of maize leaf diseases is very beneficial for managing the maize crop and gives clear signals for early detection and disease prevention [7]. The manual approach to identifying maize leaf disease is challenging because it requires considerable effort and constant daily observation. Thereby, a manual procedure has a high rate of inaccurate disease identification [8].

Deep learning technology has advanced quickly in recent years. In particular, Convolutional Neural Networks (CNN) have been frequently used to detect plant leaf disease [9]. It is more effective than conventional approaches and has superior generalization ability because of its end-to-end property, which frees it from the need for labour-intensive image pre-processing and manual feature selection [10]. The proper number of features, pre-processing, and recognition using machine learning algorithms are only a few of the processing stages that researchers have uncovered for various computer vision systems [11-12]. The selection algorithms and features fusion that has received a lot of attention in computer vision in recent years are introduced, along with several related strategies that increase the system's recognition accuracy [13]. Deep-extracted features, form, color, and texture are the primary feature extraction techniques employed in recognition [14]. However, a collection of features performs better than a single feature type. It consists of the following three fundamental steps: “classifier classification”, “feature extraction and feature fusion”, and “picture contrast enhancement”. The results from the experiments indicate that opting for specific features can enhance the accuracy of the system's recognition capabilities.

The following is a description of our work's main contributions:

1. Pre-processing includes contrast enhancement and data augmentation.
2. Present a new DFLM model using the merging of three deep learning models such as VGG-19, Inception V4, and ResNet152 V2 for the classification of maize leaf diseases.
3. Implement a single and fusion model on the maize leaf image dataset.
4. Analyze the differences in evaluation performance between individual models and fusion models.

The subsequent sections of the paper cover the following topics: Section 2 delves into the discussion of related research for the detection and categorization of maize diseases of the leaves; Section 3 is crucial since it outlines the suggested contribution to the model; Section 4 explains the results part of the disease categorization based on several metrics of evaluation with result and discussion in section 5. Finally, section 6 discusses the conclusion and future scope.

2 Related Work

To classify, identify, and collect characteristics associated with plant diseases, researchers have offered several methodologies. To achieve this, DL has been widely used in the agriculture industry, along with image processing and traditional ML techniques. An effective and efficient approach to early identification and diagnosis of plant diseases has been the focus of growing research in the field of automated plant disease detection in recent years. The output and quality of plants are seriously threatened by plant diseases, which have been the subject of many studies.

Muhamad et al. [15] proposed a mixed approach to combining features for the identification of coffee leaf disease. This method involves integrating features at both early and late stages of the process. The hybrid models combine MobileNetV3, Swin Transformer, and variational autoencoder (VAE) to extract the information feature from the input images. The dataset of Robusta coffee leaves (RoCoLe) with different types of diseases, such as red spider mite infestation and leaf rust disease is used to test the suggested hybrid feature fusion approach. The accuracy of the hybrid feature fusion is 84.29%, outperforming the performance of the individual models. Momina et al. [16] implementing spatial-channel attention into the ResNet-50 model to serve as its foundational network, have provided an improved Faster-RCNN technique. MaizeNet is recommended for the precise localization and categorization of several maize crop leaf diseases. There are 2112 photos in all, each having a resolution of 3000x3000 pixels. The average accuracy rating for the MaizeNet model is 97.89%. Yadav et al. [17] have suggested an idea for classifying various leaf diseases. They have collected 8750 images from the PlantVillage dataset and classified them into 23 classes. The procedure entails gathering the photos, pre-processing, feature extraction, feature selection, and classifying plant diseases. A deep convolutional network has been used to extract the features. They have extracted 100 features from AlexNet after removing the 1000-way SoftMax layer. Using the suggested Particle Swarm Optimisation, the 34 best descriptive features are chosen from these features and achieved an accuracy of 97.39%.

Haque et al. [18] have created a categorization system for healthy and diseased maize leaves. They have collected 5939 images from “ICAR-IIMR” institute, Ludhiana, India. The key point vector was then calculated, and classification was executed employing an InceptionV3 model integrated with an average pooling layerand the system outperforms with an accuracy rate of 95.99%. Zeng et al. [19] introduced a CNN basic model called “SKPSNet-50” to detect various maize leaf diseases early. To address the issue of data imbalance, this study used the combined focal loss function as a reference for model parameter adjustment. The suggested model performs better than the SKNet-50 model in identifying photos of natural scenes displaying six different types of maize diseases, with an average identification accuracy of 92.9%.

Sharada et al. [20] took around 54,306 images of healthy and diseased plant leaves from the PlantVillage dataset. The GoogLeNet models attained an accuracy level of 99.34%. Saleh et al. [21] collected 4188 images with three classes and images of maize leaf diseases were taken from various online data sources. They created EANet, a concise CNN model that utilizes the EfficientNetv2 CNN model alongside an attention mechanism. This was designed to accurately detect various diseases affecting maize leaves. The method put forward attains an overall accuracy of 99.89% during training and 98.94% during testing. Rajeev et al. [22] collected 929 images of two different diseases. The proposed AlexNet model's ability to quickly and accurately identify leaf disease in maize plants. 3 max-pooling layers and 5 convolution layers were employed in the suggested AlexNet model. The suggested AlexNet CNN model was optimised using a loss function. The proposed model outperforms with an accuracy of 99.16%.

Pan et al. [23] gathered a collection of 30,655 images originating from Jilin Province and the greenhouses situated in the College of Plant Science at Jilin University. These images span the years from 2017 to 2019.with six diseases along with healthy. AlexNet, GoogleNet, VGG16, and VGG19 are four different DCNN models that have been trained, tested and validated. The GoogleNet model has the highest accuracy of 99.94% among DCNN models for detecting maize diseases. Hassan et al. [24] collected 15408 from the PlantVillage dataset. They recommended employing EfficientNetB0 and DenseNet121, both of which are pre-trained convolutional neural networks (CNNs) used to capture detailed features from images of maize plants. The findings of this research were then juxtaposed with outcomes from different pre-trained CNN models, such as InceptionV3 and ResNet152. These models come with increased parameters and require more computational resources in contrast to the proposed method. The recommended model attained a superior classification accuracy of 98.56%, showcasing its outperformance over ResNet152 and InceptionV3, which achieved classification accuracies of merely 98.37% and 96.26%, respectively.

Helong et al. [25] collected 2516 images of 6 different classes and after applying augmentation techniques the images were increased to 14,245. They suggested an MSOResNet (multistep optimisation ResNet) model for identifying apple leaf diseases. The system performs an accuracy of 95.7%. Jianwu et al. [26] suggested a simple CNN model named GrapeNet for identifying various symptom stages for particular grape diseases. GrapeNet is composed of three primary components: convolutional block attention components, residual units and blocks for merging residual features. When compared to other traditional models, the GrapeNet model achieved the best classification results.

Despite the presentation of multiple Deep Learning based maize leaf disease detection models, there is still a need to enhance detection rates and thus plant survival rates. Most of the studies concentrate on frequently occurring diseases in maize leaves, while only a limited number of research papers address all categories of diseases. There has been no prior research dedicated to developing a fusion learning model specifically tailored for classifying various types of diseases affecting maize leaves.

3 Material and Methods

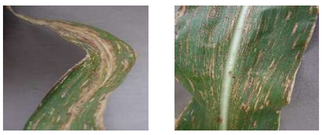
This section begins by collecting the dataset using some data pre-processing and augmentation techniques. Additionally, the classification models undergo training and testing using the provided dataset. As per the gaps observed in the literature analysis, the timely detection of lesions on maize leaves holds significant importance for optimizing pest management and the appropriate utilization of fertilizers. Failure to accurately recognize these biological stresses could lead to farmers obtaining low-profit yields despite their dedicated endeavours. To detect lesions, inform farmers, and enable early diagnosis, several image-processing techniques have been created.

3.1 Dataset Collection

Images of maize leaves employed to assess the effectiveness of diagnosing biotic diseases are collected from secondary origins and the Plant Village dataset[27] (accessed on 1 December 2022). Table 1summarises the class of maize disease with the count of images and symptoms which will cause due to different biotic stress. Humidity, pests, heat, minerals, microorganisms, and fluids collectively impact the disease spots appear on maize leaves.. The process of data collection plays a crucial role in real-time operations due to its potential to impact the experimental results negatively if inaccurate data is present within the dataset. As a result, the common norm should be expressed and followed during the data collection process. The entire dataset is divided into two subsets, with the ratio of training to testing being 80:20. The collection includes images of healthy maize plant leaves together with five kinds of diseased leaves.

Table 1: Description of the dataset with symptoms

Disease Class Name	**Number of Images**	**Symptoms**	**Caused due to**
“Common Rust”	555	Dark brown with pustules on both sides	Fungus
“Southern Rust”	625	Oval-shaped lesions turn green to yellow	Fungus
“Gray Leaf Spot”	625	Lesions begin as small dot spot	Fungus
“Maydis leaf blight (MLB)”	590	The dark brown color of the lesion on the upper part of a leaf	Fungus
“Turcicum leaf blight (TLB)”	570	Brownish grey lesion spot	Fungus
Healthy	760	--	

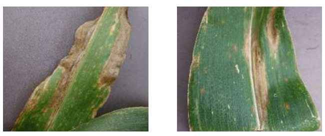


(a)

(b)

(c)

(d)



(e)

(f)

Figure 1. Few samples of maize leaf image dataset(a) grey leaf spots, (b) common rust, (c) maydis leaf blight, (d) southern rust, (e)turcicum leaf blight, (f) healthy.

It contains 256×256 colored JPEG-labelled images. This study focuses mostly on the biotic diseases that affect maize crops. As a result, 3725 photographs in total were gathered, of which 700 images with healthy leaves were chosen for this work from the primary repository and 3025 images from the secondary source, as shown in Figure 1. It shows different sample images of the maize leaf disease dataset. The sample dataset contains images of grey leaf spots, common rust, Maydis leaf blight, Southern rust, Turcicum leaf blight, and Healthy.

3.2 Data Pre-processing

Three pre-processing steps includes resize, contrast enhancement, augmentation, and feature extraction with classification are done using the proposed DFLM model. The Maize Leaf Disease collection has images of 256 ×256 ×3 pixels that were reduced to 224 ×224 ×3 pixels using the CLAHE method.

3.2.1 Contrast Enhancement

In terms of the intensity of maize images, CLAHE has proven to be the most useful. The major goal of this model is to make it simple for the spectator to look at the diseased image. It is used to rank the given pixel intensities in the pertinent histogram by looking at the histogram intensities in the contextual area placed at each pixel. The histogram can be thought of as an enlarged version of the conventional histogram in which a model seeks to boost contrast to a user-selectable extent at each intensity level. CLAHE successfully increases the local information of a picture by using a classic contrast-enhancing method. When compared to actual photographs of maize, CLAHE is mostly used to increase contrast in an image.Algorithm 1 outlines the process of applying CLAHE for contrast enhancement as part of the pre-processing phase in the study for diagnosing multiple maize leave diseases.

Algorithm 1: Contrast-Enhancement for Maize Leaf Dataset (CE-MLD)

Input: Maize Leaf Dataset $\{Z = z_{1,}\ z_{2 \ldots\ldots\ldots\ldots\ldots} z_n\ \}$Here, n reperesents the number of images in the dataset.

Output:$C_o(x_i)$as contrast-enhanced image

1. Load the leaf dataset, which consists of a frontal view of the images labelled with six different classes of diseases.
2. Set$Z = z_{1,}\ z_{2 \ldots\ldots\ldots\ldots\ldots} z_n$where n is the number of images of the datasetz_i
3. Convert z_i as $H_s(i)$ as greyscale image
4. Do
5. If $(\boldsymbol{H_s(i)\ as\ i \neq 0})$0
6. Print →$z_n$is RGB colored image

7. else
8. Print →z_n is an image $H_s(i)$ and divide the non-overlapping regions as $8\ \times 8\ or\ 16 \times 16\ pixels$.
9. Set $H_s(i)$ as the "histogram" as $H_{ol}(i), and\ H_{ol}(j), i\ \in\ \{1, 2, \ldots, r\}$ and $'r'$ is the total number of tiles.
10. Clip $C_o(x_i)$=$H_{ol}(i)H_{ol}(j), = clip\,(H_{ol}(j) \times\ r$.
11. Return→$C_o(x_i)$

Table 2 presents the key parameters and descriptions for the Contrast-Enhancement for Maize Leaf Dataset (CE-MLD) algorithm. It takes the maize leaf dataset as input and outputs a contrast-enhanced dataset.The contrast limit for the histogram equalization in CLAHE ranges from 1 to 4, and the interpolation method used for combining histograms of neighbouring tiles is bilinear.

Table 2. Key Parameters and Descriptions for the CE-MLD

Name of Parameter	Description of Parameter
Z	Maize Leaf Dataset
$H_s(i)$	Grey Scale image
$8\ \times 8\ or\ 16 \times 16\ pixels$	non-overlapping regions
$H_{ol}(i),$	Histogram division in set i subset of a dataset
$H_{ol}(j),$	Histogram division in set $j subset$ of a dataset
$C_o(x_i)$	Contrast-enhanced image
$clip(H_{ol}(j) \times\ r$	Clipped non-overlapping regions of the dataset

3.2.2 Data Augmentation

For data enhancing the data augmentation technique is used which also lowers the risk of overfitting after dataset pre-processing and splitting. The strategies also take advantage of geometric transforms like flips and random rotations. Random rotation and up to 90 degree movement of the images is applied, and 180 degrees indirection [28]. By doing this, the models used in this work become more resilient to changes in position and orientation and have a decreased risk of over-fitting. After augmentation the data gets count to 14,900 images.

(a) Maydis leaf blight

(b) Gray leaf spot

Figure 2. Samples images of maize leaf dataset after augmentation.

3.3 Proposed Deep Fusion Learning Model (DFLM)

The DFLM model is designed with the fusion of three pre-trained models that demonstrate higher accuracy in compared to other models for the detection and classification of maize leaf diseases. The models are discussed in the sections below.

3.3.1 VGG19

The VGG19 model's input is a 224×224 picture with 3 channels and a mean RGB value removed. It has 19 layers with weights made up of 16 convolutional layers and 3 fully connected (FC) layers.

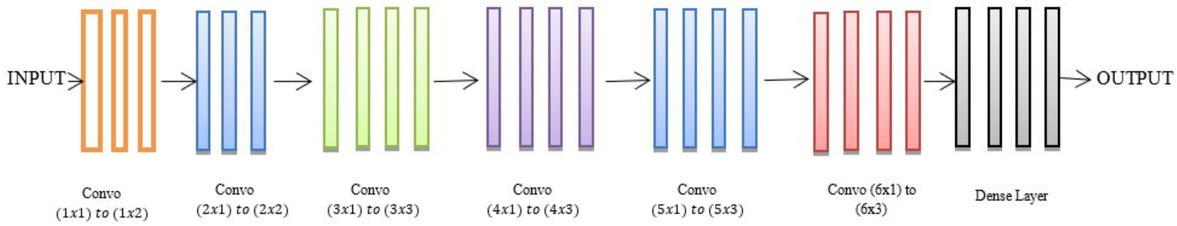


Figure 3. VGG19 model architecture

The kernel size of the convolutional layers is only 3×3, while padding and stride are also 1 pixel. The network is composed of five max-pooling layers with a stride comprised of two pixels and its kernel size of two by two. Depending on the network, the training takes two to three weeks [29]. The weights were trained and initialized gradually, beginning with random initialization in a network with fewer layers then, after training, moving the parameters to a bigger network. They repeated this process until they reached the network with 19 layers. This is observed that VGG 19 model without any normalization layers is not improved by employing local response normalization. Second, this work sees that the ConvNet depth increases from 11 layers in input to 19 layers in the classification error.

3.3.2 Inception V4

Figure 4 depicts the Inception V4 deep learning model for classifying pictures, which is built on convolutional neural networks. Without allowing the amount of parameters, to enable deep networks to go out of control, Inceptionv4 was created [30]. Compared to 60 million for AlexNet, Inceptionv4 contains "less than 25 million parameters". Convolution, max pooling, fully connected layers, and dropout are the symmetric and asymmetric components of the model. Batch normalisation, which is used extensively in the model and is also applied to the inputs for activation, is used. Softmax is used to determine the loss.

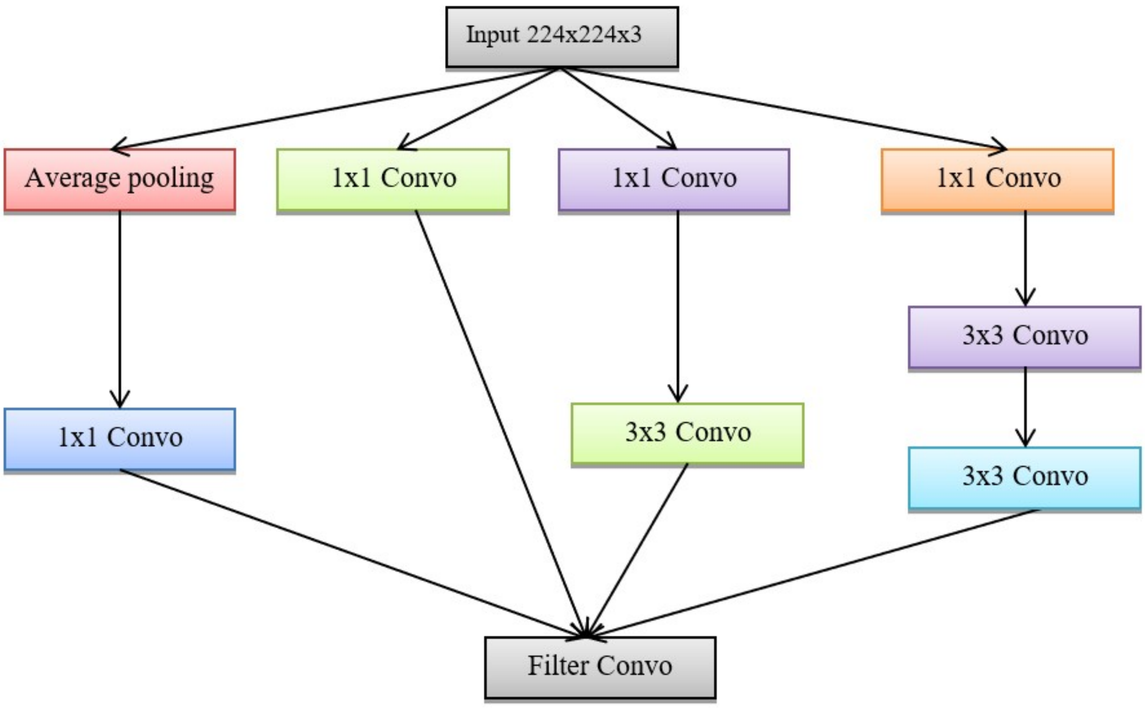


Figure 4: Inception V4 model architecture

The Concat batch size

$X_i = \delta y_i + \gamma$ where $i = 1,2,3 \ldots \ldots n$ (eq. 1)

And δ *and* γ is a fixed constant learning parameter with batch variance.

3.3.3 ResNet152 V2

ResNet-152 V2 represents a member of the ResNet (Residual Network) family, encompassing a deep convolutional neural network (CNN) architecture. It is an advanced version of the original ResNet-152 model, which introduced residual connections to address the problem of vanishing gradients in deep neural networks. ResNet-152 V2 further refines the architecture to improve performance and accuracy [31]. Using residual blocks, which allow the network to acquire residual functions instead of directly learning the required fundamental mapping, is the core concept behind ResNet models. This helps alleviate the deterioration issue that happens when larger networks begin to function poorly than shallow networks due to the vanishing gradient issue. The 1x1 convolution layers are responsible for reducing and then increasing the dimensionality of the input, while the 3x3 convolution layer performs the main feature extraction as shown in Figure 5.

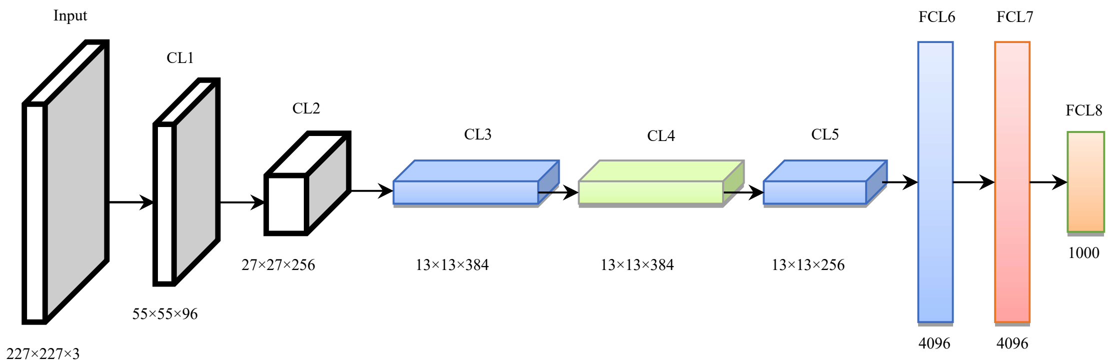


Figure 5. ResNet152 V2 model architecture

3.3.4 Proposed Model

The classification method is improved in this study by applying the DFLM model, which also makes it possible to recognize six different diseases from maize leaf images. Because a single modality would be insufficient to provide an efficient identification rate, the combination of all three models using decision-based multimodal integration improves the detection rate. The advancements in unimodal CNNs are advantageous in DFLM design, and substantial development has been done. There are 256,512 characteristics in total in the fusion model. In the most recent research, fusion approaches have been shown to be among the most efficient and dependable strategies. It may be applied to accomplish a variety of objectives, including as lowering model variance, raising prediction accuracy, and lowering bias. Figure 6 illustrates how a fusion strategy is used to merge the data from many prediction models into a new model.

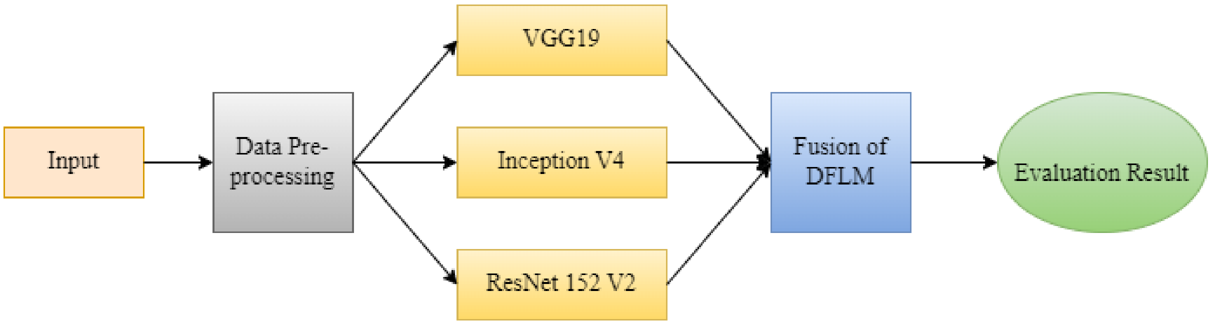


Figure 6: Proposed Fusion model architecture

A number of CNN models that have already been trained, including VGG19, Inception V4, and ResNet152 V2, which exhibits greater than 90% accuracy, were employed to develop the fusion model in this work. The recommended strategy is thoroughly justified by the algorithm. Let M represent the group of previously trained models, consisting of VGG19, InceptionV4, and ResNet152 V2. Grey leaf spot, Common rust, Maydis leaf blight, Southern rust, Turcicum leaf blight, and Healthy are just a few of the six classes of maize plants that can be found in the dataset (X_i, Y_i), which contains RGB images of both healthy and diseased plants in each class $224 \times 224 \times 3$. This data is employed to refine every model within the fusion technique. In order to enhance the effectiveness of deep learning techniques and reduce the potential negative impact of experimentation, the training dataset is segmented into smaller batches, each containing 'n' instances as specified in equation 1.

$$A(v, W_i) = \frac{1}{b}\sum_{y\in X_i, z\in Y_i} t(l(y, v), z) \qquad \text{Eq. (1)}$$

Although ridge regression is another name for the L2 regularizes in equation 2, overfitting and feature selection are also used. Ridge regression modifies the aforementioned loss function by including a component for the magnitude of the coefficient raised to the power of two. If the delta is high, the weight is excessive and the fit is poor. The value chosen for this job was 0.001.

$$L2 = \delta\sum_{x=1}^{p}\partial_x^2 \qquad \text{Eq. (2)}$$

The outcomes of many techniques' forecasts are combined using the fusion methodology to provide a cohesive result. The fusion strategy, which combines the projected scores of several models, ensures greater accuracy. In Equation 3, the recommended fusion result is presented as follows.

$$x^* = \arg max_i \frac{\sum_{\int B} l(u, x_{test})}{|A|} \qquad \text{Eq. (3)}$$

Algorithm 2 describes the procedures used to identify and categorise illnesses in maize leaves using a fusion learning technique.

Algorithm 2: Proposed Deep Fusion Learning Model (Proposed DFLM)

Input: T_{RGB}
Output: Classification Result (R_c)

1. Take input T_{RGB}as $256 \times 256 \times 3$and resize as $224 \times 224 \times 3$.
2. Use appropriate pre-processing methods to prepare the images.
3. Set a model as Z= {VGG19, InceptionV4, and ResNet152 V2}.
4. A (38×1) dimension layer is used in place of the last layer of the fusion model.
5. For each model in Z do
6. the specified learning rate = 0.0001.
7. epochs = 1-50
8. for every single batch $(A_i, B_i) \in (A_{train}, B_{train})$ do
9. the parameters of pre-trained model in Z
10. stop
11. stop
12. stop
13. follow the step below for each a $\in A_{test}$
14. combining the information derived from all model in Z
15. stop
16. Return → O (Classification Result)

The 256 x 256 x 3 collection of images of maize leaves was downsized to 224 x 224 x 3 using this suggested model for improved detection precision. The dataset is pre-processed using several models. A pre-trained prototype is then switched into the last layer of the fusion model. Each model's learning rate using the Adam optimizer is 0.0001. 50 epochs are utilised, in a batch of 32. For data accuracy, outcomes of all the models are merged and established within a single model.

4 Experimental Evaluation

4.1 Experimental Setup

The analyses, conducted through Python programming, were grounded in these procedural conditions: the maize leaf image data is partitioned into training and testing, employed the dataset for maize leaf disease. Check to be sure that none of the test-image selections were utilised in training. Resize, remove noise from, and optimise the supplied photos using additional pre-processing methods. The images within the dataset were resized to dimensions of 224x224 to facilitate the procedure for training deep transfer learning models. A batch of 32 and a total of 50 epochs were employed for this purpose. The deep learning backend utilizes Tensorflow and Keras. Training and testing procedures were conducted utilizing the NVIDIA Tesla P40, which is equipped with 24 GB RAM. Specifics are outlined in Table 3.

Table 3: Experiment configuration details

Parameter Name	Values
The ratio for partitioning the dataset	*80: 20*
Size of the image	224×224
The rate at which the model learns	0.0001
Sample/Batch size	32
The count of epochs	50

4.2 Quality Assessment

The analysis and comparison in the present study involve evaluating both the DFLM and a solitary pre-trained model based on a set of five assessment criteria. Precision, Recall, F1-Score, Specificity, and Accuracy are the metrics employed in the analysis. False Positives show the constituents of both healthy and damaged maize leaves [32], False Negatives refer to pixels representing diseased maize leaves situated within the factual area of the leaf's actual condition, yet the algorithm fails to detect them. On the other hand, True Negatives accurately anticipate the site of the leaf disease [33]. True Positives indicate the precise and correct prediction of both healthy and disease pixels on the maize plant.

$$\mathrm{Pre} = \frac{\mathrm{True_p}}{\mathrm{True_p} + \mathrm{False_p}} \qquad \text{Eq.(4)}$$

$$\mathrm{Re} = \frac{\mathrm{True_p}}{\mathrm{True_p} + \mathrm{False_n}} \qquad \text{Eq. (5)}$$

The term "precision" refers to a performance metric that measures the accuracy of the model in correctly identifying positive cases (i.e., detecting leaf diseases) out of all the instances it predicted as positive mentioned in equation (4). According to equation (5), recall, also known as true positive rate or sensitivity, is a performance metric that gauges a models capability to correctly identify positive cases (i.e., detect leaf diseases) out of all the actual positive cases present in the dataset [34].

$$\mathrm{F1-Score} = 2 \times \left(\frac{\mathrm{Pre \times Re}}{\mathrm{Pre+Re}}\right) \qquad \text{Eq. (6)}$$

The F1-Score in the equation stands for the harmonious average of precision and recall (6) represents the result of determining the effectiveness of diseased areas in the data set. Accuracy is one of the factors considered when rating the classification model. It commonly refers to a measurement of the degree to which a positive detection is produced by the neural network, and equation (7) explains how to calculate this degree.

$$\mathrm{Acc} = \frac{\sum True_p + \sum True_n}{\sum True_p + \sum True_n + \sum False_p + \sum False_n} \times 100 \qquad \text{Eq. (7)}$$

The real negative values discovered by a model are computed using specificity. Equation (8) is used in this case to represent the negative values [35] the majority of the time.

$$\mathrm{Specificity} = \frac{\mathrm{True_n}}{\mathrm{True_n} + \mathrm{False}_p} \qquad \text{Eq. (8)}$$

5 Result and Discussion

This section discussed the experimental result shown by the different models and compared them with the proposed fusion model.

5.1 Result of a pre-trained model

The accuracy of the pre-trained model VGG19 improved from epoch 0 to 40 until it reached values of 96.12% and 94.09% for training and testing, respectively. It has 19 layers and 138 million trainable parameters. After this epoch, the accuracy curves with the Adam optimizer depicted in Figure 7 is reliable and consistent at 98% for the set of train data and 95.21% for the test data.

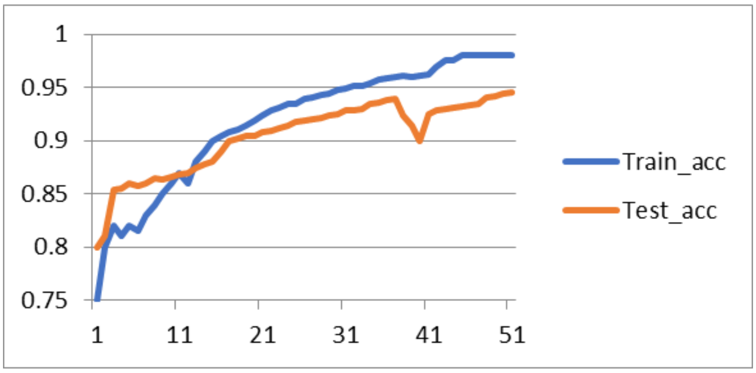


Figure 7. Accuracy graph of VGG19

The accuracy curve for InceptionV4 which was created from the training data is growing swiftly and achieves a value of 91.58%. There are 43 million parameters in the InceptionV4 model. After epochs 11 to 40, the training accuracy enters the stability stage, when it is equivalent to 95.17%. The accuracy decreases and reaches 97.13% after epoch 40 shown in Figure 8. With three hidden layers and 60 million trainable parameters, the ResNet152 V2 model has a bottleneck design and displays an accuracy of 93.93% from epoch 0 to 10 shown in Figure 9. It is also noticeable that the accuracy of training data is increasing quickly.

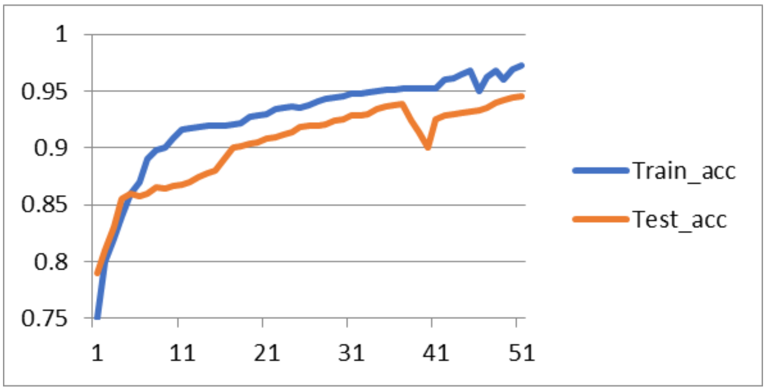


Figure 8. Accuracy graph of Inception V4

The accuracy then decreases until the training is complete, at which point it equals 96.25%. The precision, recall value, specificity, and F1-score for each pre-trained model are computed through an assessment of model performance. The model's accuracy with VGG19 was 98%, and it displays an F1-score of 93.58%, which is significantly higher than that of other models.

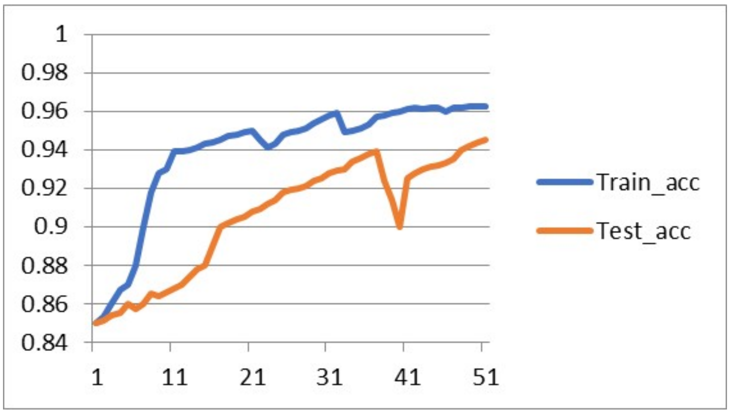


Figure 9. Accuracy graph of ResNet152 V2

5.2 Result of Proposed Model

This investigation focuses on a range of deep learning models, aiming to determine if their architecture leads to improved performance metrics. When compared to other pre-trained models such as InceptionV4 and ResNet152 V2, VGG19 stands out with higher accuracy. The proposed fusion learning model surpasses alternative models in accuracy, achieving a remarkable period of 79.45 seconds, significantly outperforming competing models. Various quality evaluations are used to assess productivity. The efficiency of the fusion learning model in comparison to a single model is being shown. With each model update, the value of the F1-score parameter changes. Figure 10 demonstrates the performance of the suggested DFLM model in a classification setting. An increase in the number of training epochs, a clear pattern emerges: the accuracy regularly grows. These findings are the result of a 50-epoch analysis. The model's accuracy clearly exceeds the 90% threshold for the full 50 epochs. This graph demonstrates that as the total number of epochs increases, so does the accuracy, proving the model's ability to enhance its categorization capabilities.

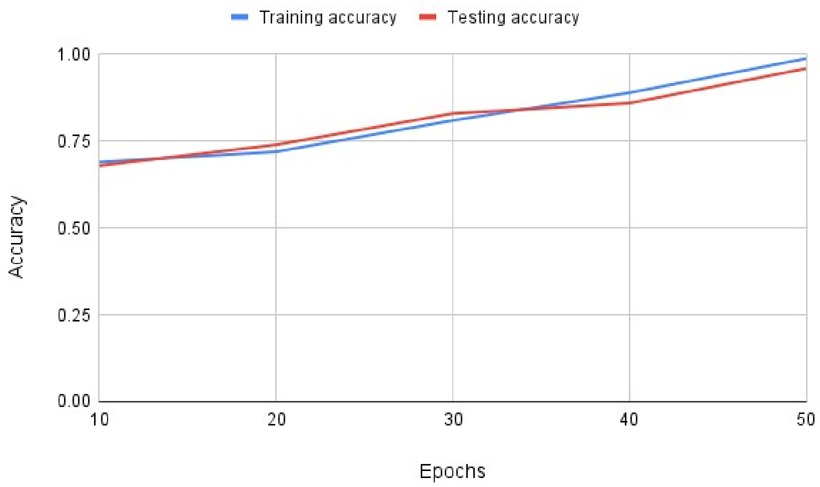


Figure 10. Proposed DFLM model accuracy

The confusion matrix for the proposed model utilising the Adam optimizer is shown in Figure 11. This matrix provides a simple representation of actual and expected labels. The class name is labelled on each column and its matching row. Turcicum leaf blight, healthy, maydis leaf blight, grey leaf spot, southern rust, and common rust are denoted by numerical values in this study, specifically 0, 1, 2, 3, 4, and 5. The DFLM model had an accuracy of 98.85%, which is significantly higher than that of pre-trained models. Precision, recall, and F1-score for the Proposed DFLM model were 97.84%, 96.11%, and 96.41%, respectively.

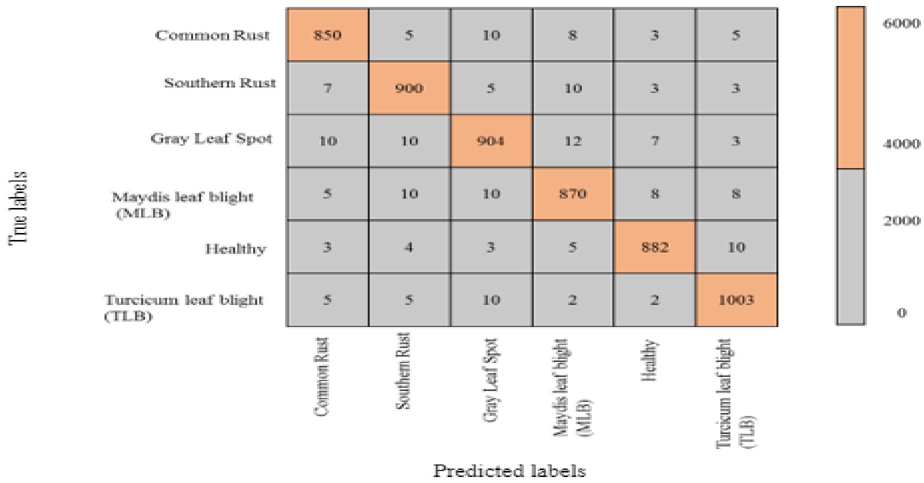


Figure 11. Proposed DFLM model confusion matrix

Table 4: Comparing models based on various performance metrics.

Model Name	Accuracy (in%)	Precision (in %)	Recall (in %)	Specificity (in %)	F1-Score (in %)
VGG19	98	94.85	94.18	98.58	93.58
InceptionV4	97.13	92.14	92.23	96.45	89.45
ResNet152 V2	96.25	92.11	91.18	96.12	90.78
Proposed model	98.85	97.84	96.11	96.58	96.41

The suggested model demonstrates an accuracy of 98.85%, %, outperforming other pre-trained models. The proposed model shows a recall of 96.11% in comparison with 91.18% of ResNet152 V2 discuss in Table 4. The VGG19 shows an accuracy of 98% with 94.85% precision and 94.18% recall. The F1-score value increases with the change of models and reaches 96.41% with the proposed model. The ResNet152 V2 shows a 92.11% precision value with 91.18% recall and shows 96.25% accuracy.

Figure 12 clearly shows the comparison of all the models in terms of different evaluation metrics. The proposed Deep Fusion Learning Model (DFLM) identifies the lesion objects with better accuracy as compared with other models. This paper employs various image-processing stages, including pre-processing, feature extraction, and classification, to detect maize leaf diseases. The small tiny lesion objects are extracted and classified using a proposed model with better accuracy in comparison with others.

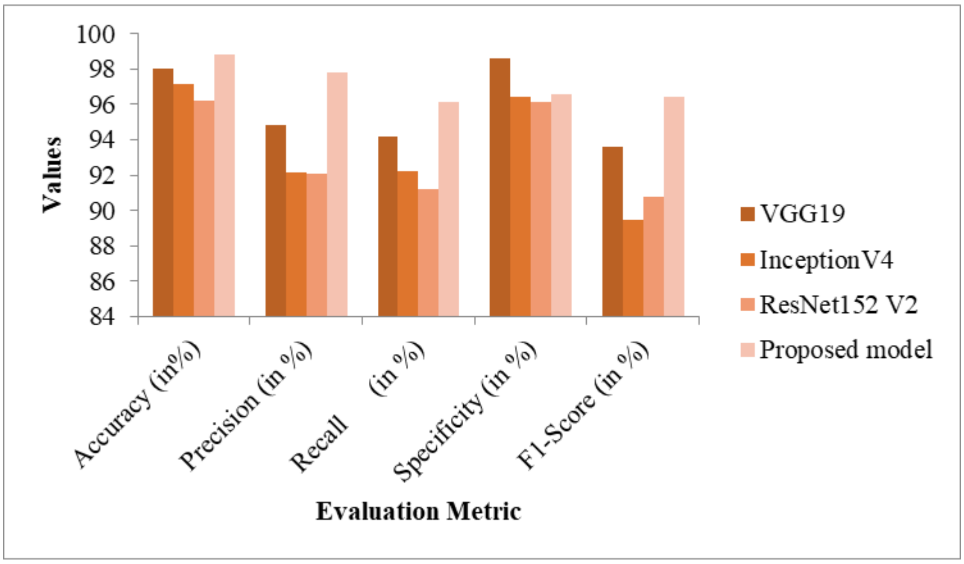


Figure 12. The performance of models evaluated across different metrics

6 Conclusion

In the study that follows, six classes of images Grey leaf spot, Common rust, Maydis leaf blight, Southern rust, Turcicum leaf blight, and Healthy are used to classify maize leaf disease using fusion and single learning models with a total of 14,900 images. In the first stage, the data undergoes different pre-processing stages with different data augmentation techniques. In the next stage, the data undergoes the entire single and proposed model where the proposed model detects the lesion objects with better accuracy. The accuracy of the model VGG19 rose from epoch 0 to 40, reaching testing and training values were 94.09% and 96.12%, respectively. The curve representing accuracy becomes comparable to 98% after the epoch, with an F1-score of 91.58%. The proposed model “Deep Fusion Learning Model (DFLM)” identifies the lesion objects with better accuracy in comparison with an accuracy of 98.85%. The fusion technique is used to combine the target's numerical data features, which go beyond the picture, with the extracted image features to increase the target's feature representation. Furthermore, a forthcoming research endeavour aims to construct an all-encompassing system for categorizing maize leaf diseases by combining feature extraction and deep learning with additional techniques including shape, colour, and texture analysis. The enhancement of performance can be notably achieved by incorporating more advanced feature extraction techniques, expanding the dataset size, and exploring alternative fusion algorithms. Additionally, multi-biotic and abiotic datasets can be added to the collection to improve disease diagnosis.

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