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A NOVEL LOSS OPTIMIZED VGG-16 APPROACH FOR CORN LEAVES DISEASE DETECTION

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ABSTRACT: Timely disease detection and management can help optimize crop yield. Corn leaf diseases, if left untreated, can lead to reduced photosynthetic capacity, premature leaf senescence, and overall plant stress, resulting in lower yields. By detecting and addressing diseases early, farmers can mitigate these negative impacts and maintain or improve crop productivity. Relevant features are necessary for machine learning models to learn from. Features can be taken from the pre-processed photos in the identification of maize leaf disease. These features could be more complex ones extracted using convolutional neural networks (CNNs), such as color histograms, texture descriptors, shape-based features, etc. CNNs primarily operate on local image patches and may lack holistic contextual understanding. CNNs may find it difficult to grasp long-range dependencies and relationships throughout the entire image for jobs that call for global context, like comprehending how various portions of a corn leaf interact to identify illness. Transfer learning offers significant advantages in terms of improved generalization, reduced training time, and handling data limitations. By transferring knowledge from pre-trained models to the target task, transfer learning can enhance the performance and efficiency of models, making it a valuable technique for corn leaf disease detection and various other machine learning applications. The proposed uses VGG-16 transfer learning approach to perform multi classification on corn leaves by reducing the losses due to the imbalance datasets.

Keywords: Neural Networks, VGG-16, Image Segmentation, Data Imbalances, Loss Function

INTRODUCTION:

While neural networks have proven to be effective in various applications, including image classification and disease detection, there are certain drawbacks associated with using them for corn leaf disease detection [6]. Among the many drawbacks, the proposed model focuses on the limitations occurred with respect to loss function. Loss functions play a crucial role in training neural networks for corn leaf disease detection, as they define the objective that the model aims to optimize during the learning process [7]. Depending on the specific task or learning objective in corn leaf disease detection, different loss functions may be needed. For example, if the goal is binary classification (disease present or not), a binary cross-entropy loss function can be suitable. If the objective is to estimate disease severity, a loss function

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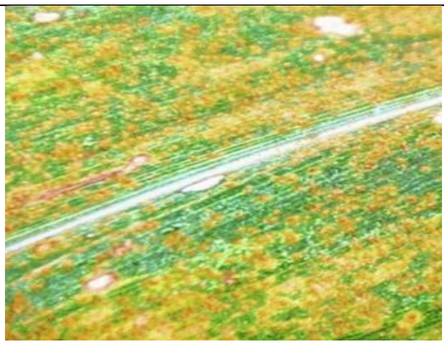
that considers the level of severity, such as a regression loss or a weighted loss, may be more appropriate.

Loss functions can help address the challenge of imbalanced datasets, where certain disease classes may be underrepresented [8]. Specialized loss functions, such as weighted loss or focal loss, can assign higher weights to minority classes or difficult samples, ensuring that the model pays more attention to them during training and avoids biased predictions. The corn disease dataset is classified into 4 categories as shown in table 1.

Table 1: Classification of bacterial diseases in Corn

Class Label	**Image Reference**	**Description**
Gray_Leaf_Spot'		GLS initially appears as small, rectangular lesions with grayish centers and dark brown borders on the leaves. As the disease progresses, the lesions enlarge and coalesce, resulting in larger, elongated grayish spots on the leaves.
Common_Rust		Common Rust appears as small, circular to elongated, raised pustules or lesions on the leaves, stems, husks, and sometimes tassels of corn plants.
Blight		Blight diseases typically manifest as sudden wilting, browning, or death of plant tissues. Symptoms can vary depending on the pathogen and host plant involved.

2. LITERATURE SURVEY:

The most important crop in India that was collected was corn, which was exported to numerous nations. Every crop will eventually become ill, thus the first stage of pest control is essential. For the purpose of identifying various corn diseases, Kshyanaprava Panda

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Panigrahi et al. [1] presented a CNN methodology. The dataset includes 3k images of maize leaves that were gathered from the Plant Village database. Infected maize leaves are divided into three categories in the dataset, while healthy leaves are represented by just one category. The prediction of corn leaf disease was done using a CNN model. IP and the CNN model were two key components in the technique. In the process of pre-processing photos, the raw data was transformed into a pre-determined format and the images were assigned class labels. A training, test, and validation set was created from the dataset. The proposed CNN model consisted of two fully connected dense layers and three convolution layers. ReLu was utilized for each layer expect final, where it utilized a sigmoid. The model included two fully connected dense layers with 128 sieve in the initial layer & four filters in the final layer. The Adam optimizer was used for weight updates.

Diseases in crop are natural and it should be cleared in the initial stage of damage. Dionis A Padilla et al [2] has introduced a two techniques CNN and OpenMP for identification of crops. The conceptual framework consists of input, process, and output components. Input is acquired from corn leaf image data parameters. The process involves image processing, feature extraction, and CNN-based disease detection. The output includes the classification of leaf diseases and the execution time rate. The input image and user as entities, with the image processed to identify the leaf disease and the output received by the end-user. The expanded system movement includes processes for classifying leaf diseases using the Raspberry Pi camera and displaying the results on an LCD touchscreen. The prototype development flowchart outlines the steps from device initialization to disease detection and result display.

Plants can be diseased in less time and it damage the whole crop in no time. S. Devi Mahalakshmi et al [3] has proposed a ML technique for identification of diseased leaves. The proposed system captures images automatically at regular intervals for pest and disease detection in corn fields. Images undergo verification against pests and diseases. Segmentation is performed using the SLIC algorithm and texture-based segmentation with Gabor filters. The ACE algorithm is used for image preprocessing, including resizing and color constancy. Chromatic/spatial adaptation is employed to adjust the appearance of each pixel based on the image content. Feature extraction involves extracting color, statistical, and texture features from the segmented images. SVM is used for pest and disease classification. BSVM identifies the presence of pests and diseases, while MSVM classifies the specific type. Pesticide and fungicide recommendations are made based on the identified pests or diseases, using a database of agricultural information. The dosage level and usage instructions for the recommended solutions are obtained.

Seasonal differences in diseases make it necessary to know them in order to use the right pest control measure. In order to achieve the best detection, Hassan Amin et al [4] used DL and TL approaches. A portion of the Plant Village dataset from Kaggle, with 217k photos total and 38 categories of healthy and unhealthy plant images, was utilized as the dataset. The Plant Village dataset subset is mostly concerned with corn plants. On the augmented training

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subset, the model is trained. DenseNet121 & EfficientNetB0 are used as baseline models in the training phase of the CNN design. These models' pre-trained weights are loaded, and the classification layers are swapped out with a fully connected layer with 210 neurons and an average pooling layer.

While harvesting the corn crop every farmer may not have the perfect knowledge about diseases so, C. Ashwin et al [5] has review both ML & DL related to corn leaf diseases. Using pre-processing, segmentation, image localization, and enhancement techniques, leaf disease detection entails examining changes and their locations in leaf pictures. To reduce extraneous data and increase prediction accuracy, pre-processing is essential. Maximal in-between class variance is the foundation of the Otsu approach to optimal segmentation. In order for machine learning methods to effectively classify data and reduce the dimensionality of the input data, feature extraction is essential. Because they are more readily available and easier to maintain than other plant parts, leaves are particularly significant. utilized edge information-based features for classification while concentrating on obtaining leaf contours using straightforward techniques like the Sobel operator and thresholding. Deep learning methodologies like CNN, Auto-encoders, RNN, & DBN have been effective for disease prediction. CNNs, in particular, resemble the human visual system and learn features automatically, while Auto-encoders focus on feature extraction, and RNNs and DBNs offer context learning and handle similarity between projections and input. Table 2 presents the analysis of the existing models.

Table 2: Analytical Approach on Existing Systems

Author	Algorithm	Merits	Demerits	Accuracy
Kshyanaprava Panda Panigrahi et al	CNN	The data was collected from all sides of INDIA.	Particular diseases can be identified.	88.78%
Dionis A Padilla et al	CNN, OpenMP	It identifies the diseased leaves in short time.	The performance can be increased.	83%
S. Devi Mahalakshmi et al	BSVM, MSVM	Along with disease the pest is derived.	The disease can be seasonal.	85%
Hassan Amin et al	CNN, Efficient Net B0, DenseNet121	This uses a hybrid model for efficient performances.	The compared results and proposed method have less change in metrics.	88.56%
C. Ashwini et al	DNN, CNN, RNN, DBN, DAE, DBM	It can be worked on different datasets related to corn	Benchmark data set was required for constructing.	88.01%

3. PROPOSED METHODOLOGY: By combining image augmentation with transfer learning, the model can benefit from the large-scale knowledge captured by the pre-trained model while being exposed to diverse variations through augmentation. This approach can enhance the model's ability to detect and classify corn leaf diseases accurately, even in the presence of limited training data and variations in leaf images. Figure 1 presents the over all model of the proposed methodology

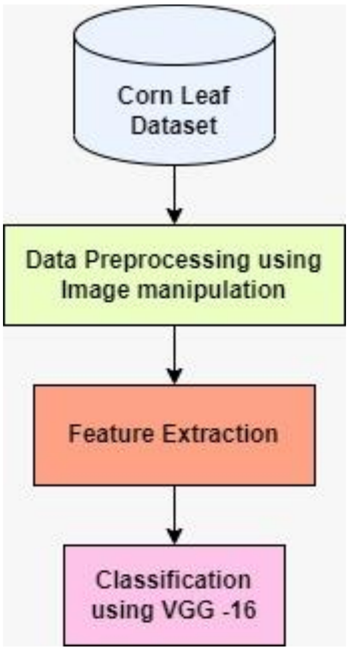

Figure 1: Classification of Corn Leaf Disease

3.1. Image Augmentation for Manipulating Image Leaves:

By performing different changes on the already-existing photos, image enhancement is a method frequently used to expand the size and variety of a given dataset. to improve the model's capacity to identify and categorise items under various circumstances. The model's generalisation and performance may be subjected to a larger range of variables, which lowers the likelihood of overfitting. During image augmentation, the original images in the dataset are modified by applying a set of transformations, such as rotations, translations, scaling, flips, crops, and changes in brightness or contrast [9]. To enhance the model's ability to recognize and classify objects under different conditions. By exposing the model to a larger variety of images, it learns to be more robust and generalize better to unseen data. Each image is randomly transformed using one or multiple augmentation techniques, creating multiple versions of the original image. By utilizing image augmentation techniques, researchers and practitioners can increase performance, generalization, & robustness of DL methodologies in computer vision tasks.

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3.2. VGG for Corn Disease Detection

The VGG algorithm is a DCNN design commonly utilized in computer vision tasks, including disease detection in plant leaves. In corn leaf disease detection, the VGG methodology can be employed to automatically analyze and classify images of corn leaves based on their visual characteristics. The process initiates with a collection of data related to corn leaf images is collected, including both healthy leaves and leaves affected by various diseases. The collected images are pre-processed to ensure consistency and enhance the algorithm's performance. Conv filters are used to extract pertinent features from the pictures during training, and pooling techniques are used to gradually shrink the spatial dimensions. The extracted features are then fed into fully connected layers, which learn to classify the images based on the extracted features. The model's performance is analyzed to identify areas of improvement or fine-tuning if necessary. Figure 2 presents the Neural Network Model of VGG-16

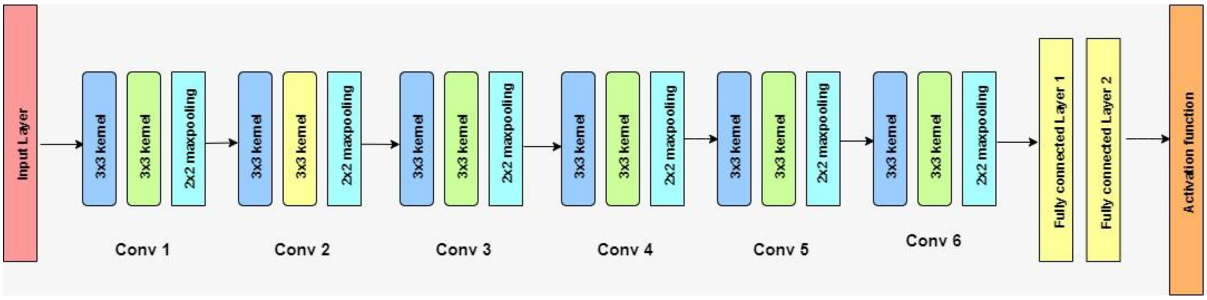

Figure 2: VGG-16 Model for Classification

3.3. Loss Functions in Neural Networks

A mathematical function called a loss function, often referred to as a function of costs or a function that is objective, is utilized in NN to calculate the error or difference between the output that is anticipated and the output that is actually produced. It quantifies how well the neural network performs during the training phase and provides a means to optimize its parameters. The MSE function of loss is one that is frequently employed in neural networks. This straightforward loss function calculates the MSE variance between anticipated and observed values. It is frequently employed in regression jobs when the objective is to forecast a continuous value. When the objective of a classification challenge is to forecast a categorical value, cross-entropy loss is frequently utilised. It calculates the discrepancy between the expected and actual probability distributions. When attempting to forecast whether a data item corresponds to class 0 or 1, which is a binary classification job, hinge loss is frequently utilised. It calculates the disparity between the score as predicted and a preset threshold.

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4. RESULTS & DISCUSSION:

Rotation **Flip** **Shear** **Zooming**

Figure 3: Image Manipulation Operations on Leaves

Figure 3 represents image manipulation operations that are commonly applied during the process of image augmentation in machine learning tasks. By applying these operations to images in the training dataset, it helps to increase the diversity of the data and improve the model's ability to generalize to different variations and perspectives of the target objects or subjects.

```
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808

block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0

block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808

block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808

block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808

block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0

flatten (Flatten)            (None, 25088)             0

dense (Dense)                (None, 4)                 100356

=================================================================
Total params: 14,815,044
Trainable params: 100,356
Non-trainable params: 14,714,688
_________________________________________________________________
```

Figure 4: Block summary of VGG-16

In figure 4, the VGG-16 architecture has a total of 16 layers, including 13 convolutional layers and 3 fully connected layers. It is characterized by its deep structure and the use of small filters to capture intricate details in the input images. Despite its simplicity, VGG-16 achieved impressive performance in various image classification challenges, demonstrating the effectiveness of deep convolutional neural networks**.**

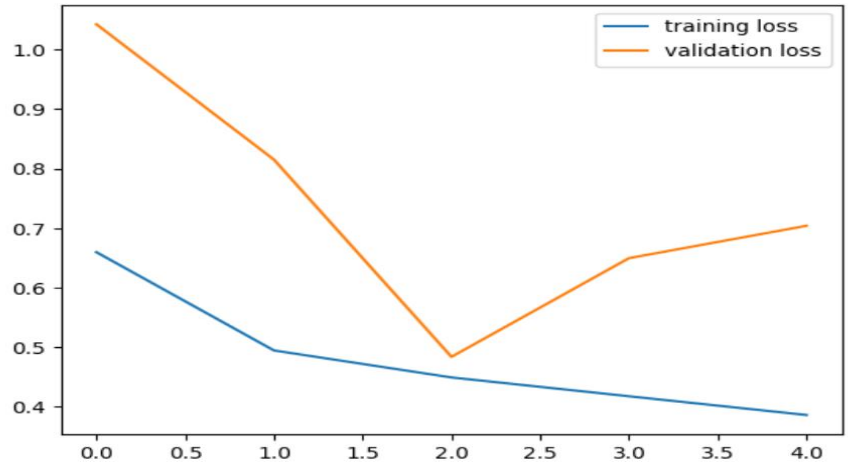

Figure 5: Loss Representation

Monitoring both the training loss and the validation loss is crucial in training machine learning models. If the training loss continues to decrease, while the validation loss increases or remains stagnant, it could be an indication of overfitting. Balancing the training loss and the validation loss is important to ensure that the model is learning to generalize well and perform accurately on unseen examples.

5. CONCLUSION: Transfer learning provides a valuable approach for corn leaf disease detection by leveraging pre-trained models and adapting them to the specific challenges of identifying and classifying corn leaf diseases. It addresses the limitations of limited labeled data and improves the generalization and performance of the models, making it a valuable technique in agricultural applications. Transfer learning has been shown to improve the performance of models in various computer vision tasks, including disease detection. By leveraging pre-trained models, the model can benefit from the learned knowledge, which can help in accurately detecting and classifying corn leaf diseases. This improved performance can lead to better disease management decisions, reducing crop losses and increasing productivity. The future of corn leaf disease detection lies in the convergence of emerging technologies, advanced analytics, and intelligent systems. By harnessing these advancements, there is great potential to improve disease detection accuracy, speed up decision-making processes, and enhance overall crop health and productivity.

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