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A Hybrid Deep Learning Approach for Crop Disease Severity Level Prediction

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Abstract: The threat of crop diseases and the need for efficient management are critical concerns, particularly in the context of maize cultivation. Early detection and accurate estimation of disease severity play a pivotal role in safeguarding maize crops and ensuring optimal yield. Convolutional Neural Networks (CNNs) have emerged as invaluable tools for this purpose, showcasing their prowess in automatic feature extraction. In the realm of maize disease severity estimation, the distinct characteristics of diseases, such as variations in lesions texture along with variations its color serve as crucial factors for automated assessment through machine learning. In this paper, a CNN model is developed with combination of transfer learning features from ResNet101 and Inception-V3 models. The features obtained from these models are then combined and passed through the attention layer ensures optimal performance. With tuning of hyper parameters and 5-fold analysis model is set for highest performance of 0.956 of accuracy. The high specificity of 0.985 shows models suitability for primary stage disease detection. This approach reflects a proactive strategy in addressing the challenges associated with disease severity estimation in maize cultivation, utilizing cutting-edge technologies for the benefit of agricultural sustainability.

***Keywords*:** *Disease Severity, Maize Crop, CNN Model, Transfer Learning, Attention Layer.*

1. Introduction

Substantial economic losses and a threat to food security are posed by crop diseases, representing a significant peril to the worldwide food supply chain. Early detection and effective management of these diseases are vital to curb their spread and minimize the resulting damages. A promising avenue for accurate and efficient detection and classification of crop diseases is provided by image-based methods. Exceptional performance in image classification tasks has been demonstrated by Convolutional Neural Networks (CNNs) within this context [1].

Substantial global crop losses are seen, resulting from diverse fungal, bacterial, and viral pathogens cause leaf diseases. Detection of disease severity at an early stage is essential for timely treatment planning and management of crops for maximum output [2]. In recent years, there has been a widespread application of CNNs in the classification of leaf disease severity in various crops, such as maize. The automatic CNN-based models excel in leaf disease severity classification, automatically extracting discriminative features from images. The CNN model based approach shows in depth feature extraction capability which provides relevant features for respective classification task and thus shows improvements over conventional features extraction methods [3].

The changes in texture, color and shape characteristics of the leaf and diseased region of the leaf are the fundamental characteristics that are to be observed while developing the CNN model. The changes with respect to disease severity in five different stages of severity are shown in Figure 1. The initial stage addresses diseases with severity levels within the range of 20%. Subsequent stages, numbering up to five, exhibit an incremental rise in severity levels, culminating in the 5th stage where severity surpasses 80%.

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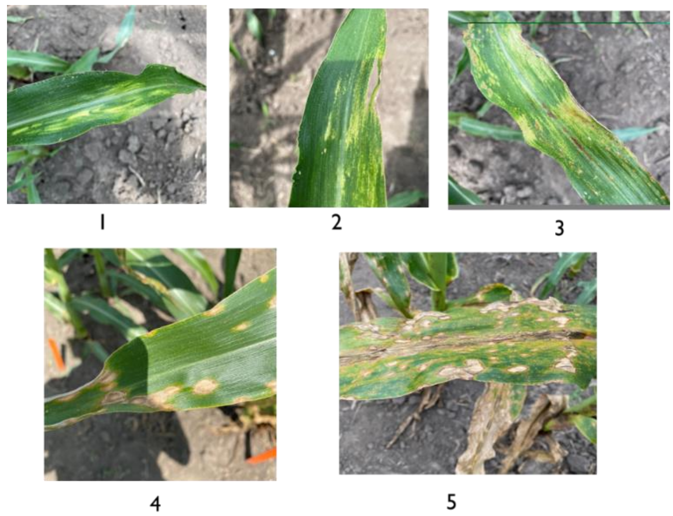

Fig 1: Five Levels of Disease Severity of Maize Leaf Disease (Leaf Blight)

In this work, initially, the standard CNN models are evaluated for selecting right models for transfer feature extraction in transfer learning mode and then two models are selected for extracting distinct but relevant features that improve the performance.

In summary the contributions of this work can be summarized as,

1. Selection of model from various standard CNN models for extracting relevant features from diseased maize leaf image. ResNet 101 and Inception-V3 are found right pretrained models for extracting features from diseased maize leaf images.
2. Development of custom CNN layers to combine the features obtained from pretrained models and applying attention layer for boosting the classification performance.
3. A hyper parameter tuned model for improved performance of severity classification of leaf blight disease in Maize crop.

2. Related Work

Simhadri et al. [4] analyzed 15 CNN models for rice leaf disease detection, highlighting Inception-V3's superior accuracy in transfer learning. This emphasizes its relevance in optimizing disease identification in rice cultivation. Yang et al.'s stacking approach combines diverse CNN architectures for potent rice leaf disease detection, while Rawat et al.'s [5] focus on ResNet50 underscores its efficacy in managing large datasets, driving innovation in agricultural technology. Mosleh et al.'s [6] accurate CNN model for potato disease detection is a breakthrough, advancing deep learning in agriculture for improved crop monitoring and early disease detection, fostering sustainable practices. Huang et al. [7] introduced DenseNet, a revolutionary architecture that addressed the challenge of information flow within CNNs. DenseNet's distinctive feature is the dense connectivity pattern, wherein each layer receives direct input from all its preceding layers, promoting efficient information propagation. This design minimizes the vanishing gradient problem and encourages feature reuse, leading to improved model performance.

Building on the foundations laid by Huang et al., Li et al. [8] extended the capabilities of DenseNet by introducing fire-FRD-CNN and mobile-FRD-CNN architectures. These extensions aimed at optimizing feature map generation, a crucial aspect in image recognition tasks. The fire-FRD-CNN and mobile-FRD-CNN architectures introduced innovative mechanisms to enhance the extraction of discriminative features, contributing to heightened accuracy and efficiency in disease detection within various datasets. In a separate development, Lee et al. [9] simplified the process of disease classification, particularly in the context of the Plant Village dataset. They employed GoogleNet-BN, an adaptation of GoogleNet with batch normalization, to streamline the classification of plant diseases. GoogleNet-BN's design incorporates batch normalization layers, which stabilize and accelerate the training process by normalizing the input of each layer. This adaptation enhances the model's generalization capabilities, making it well-suited for tasks such as disease classification in diverse plant species.

Building upon the concept of ensemble learning, Simhadri et al. [4] conducted an extensive analysis of 15 different CNN models in a transfer learning framework for rice leaf disease detection. Transfer learning involves utilizing knowledge gained from one task to improve the performance of a related task, and in this context, it proved to be a valuable strategy. Among the models evaluated, Inception-V3 emerged as the most effective in terms of accuracy for rice leaf disease detection. Inception-V3's success highlighted the significance of selecting an appropriate CNN architecture, especially in the context of transfer learning, to optimize disease detection in rice leaves.

Yang et al. [10] introduced a novel stacking approach in CNN-based rice leaf disease detection. This method involved the combination of multiple CNN architectures, including AlexNet, ResNet50, and MobileNet-V3, aiming to leverage the unique strengths of each model. Through the stacking approach, Yang et al. observed improvements in the performance of these individual models. This innovative technique showcased the potential of ensemble learning in enhancing the overall accuracy and robustness of rice leaf disease detection systems.

Rawat et al. [5] contributed to this area by employing the ResNet50 model for the detection of rice leaf diseases. Notably, their study utilized a substantial sample size of 4000 images, emphasizing the robustness of ResNet50 in handling large datasets for accurate disease identification. ResNet50, known for its deep residual learning capabilities, addresses challenges related to vanishing gradients in deep neural networks, making it well-suited for complex image recognition tasks.

Qian et al.'s [11] work introduces the utilization of a self-attention mechanism in CNN models for maize leaf disease identification. Self-attention mechanisms allow the model to weigh the importance of different parts of the input sequence, enhancing its ability to capture relevant features. Applying this mechanism to CNNs for disease identification in maize leaves signifies a nuanced approach to feature extraction, potentially improving the model's capacity to discern intricate patterns associated with different diseases.

In the context of maize leaf disease detection, Ma et al. [12] proposed a transfer learning approach, leveraging pre-trained models to enhance the efficiency and effectiveness of disease identification. Transfer learning involves using knowledge gained from one task to improve performance on a related task, a strategy particularly valuable when working with limited labeled data. Ma et al.'s approach contributes to the broader effort of optimizing model training in scenarios where datasets for specific agricultural diseases may be limited.

Li et al. [13] contributed to the field by emphasizing the importance of compact and accurate models through the introduction of CNNPruner. This tool aligns with the growing demand for more efficient neural network architectures, particularly in applications where computational resources are limited. The CNNPruner methodology focuses on identifying and removing redundant or less critical network components, resulting in models that are both resource-efficient and maintain high accuracy.

Singh et al. [14] proposed a novel approach by combining pruning and fine-tuning to enhance the efficiency of CNN models. Pruning involves removing unnecessary parameters, while fine-tuning refines the model's weights to maintain or improve accuracy. The joint application of these techniques allows for streamlined models that maintain high performance, addressing the critical balance between efficiency and accuracy.

Kundu et al. [15] developed a comprehensive deep learning framework for maize disease detection, severity prediction, and crop loss estimation. Li et al. [16] proposed a CNN-based method with multi-scale feature fusion for precise maize leaf disease detection, incorporating innovative attention modules and fine-tuning spatial pooling.

In the ever-evolving landscape of plant disease severity estimation, Faye et al. [17] (reference not provided) conducted an exhaustive review, spanning Image Processing Techniques (IPT), classical Machine Learning (ML), and Deep Learning (DL) algorithms. Their comprehensive analysis aimed to uncover the limitations and potential challenges associated with plant disease severity assessment methodologies, shedding light on the nuances of each technique. The work by Faye et al. [17] provides a valuable synthesis of the existing solutions, offering insights into the diverse approaches employed in plant disease severity estimation. By encompassing a wide spectrum of methodologies, from traditional image processing to advanced machine and deep learning algorithms, their review serves as a compass for researchers and practitioners navigating the complex terrain of plant pathology.

Building on this foundation, Shi et al. [18] contributed a meticulous study that delved specifically into the realm of Convolutional Neural Network (CNN)-based plant disease severity assessment. Their research focused on 16 selected papers, collectively offering a rich landscape of CNN applications in this domain. The analysis covered classical CNN frameworks, improved architectures, and CNN-based segmentation networks, providing a nuanced comparative evaluation that outlined the strengths and weaknesses of each approach. Shi et al.'s study represents a focused exploration into the nuances of CNN-based methodologies, recognizing the pivotal role these deep learning architectures play in advancing plant disease severity assessment. By dissecting various CNN frameworks and segmentation networks, the researchers contribute valuable insights into the specific attributes that make each approach effective or pose challenges in the context of severity estimation. The combined efforts of Faye et al. and Shi et al. offer a panoramic view of the advancements in plant disease severity estimation methodologies. Faye et al.'s review sets the stage by encompassing a broad spectrum of techniques, while Shi et al.'s focused analysis on CNN-based approaches adds depth and specificity to our understanding. Together, these studies contribute to the ongoing dialogue on the most effective and robust methodologies for assessing the severity of plant diseases, a crucial element in safeguarding agricultural productivity.

The work presented in this paper emphasizes on severity estimation addresses a significant limitation in existing methods, enhancing the practical utility of plant disease detection models. The inclusion of severity estimation is pivotal for advancing precision agriculture, enabling more targeted and efficient management strategies, ultimately contributing to sustainable crop production and food security.

3. Methodology

Maize leaf disease severity estimation involves the comprehensive analysis of various features to accurately gauge the extent of damage caused by diseases. Key indicators contributing to this assessment include lesion size and distribution, where larger lesions or higher density correlate with more severe infections. Changes in leaf color, texture variations, and the degree of necrosis provide valuable insights into the physiological impact and severity of the disease. Additionally, features such as lesion shape and morphology, spatial distribution, leaf area affected, progression over time, overall plant health, and environmental conditions contribute to a nuanced understanding of disease severity in maize leaves. Integrating these factors enhances the precision and holistic evaluation of maize leaf diseases. An integrated analysis of these features, possibly facilitated by advanced imaging techniques and machine learning algorithms, can provide a comprehensive understanding of disease severity in maize leaves. Combining visual observations with quantitative data on these features allows for a more accurate and nuanced assessment, aiding in effective disease management strategies.

Predicting disease severity can be approached through both regression and classification methodologies, each tailored to address specific aspects of the problem. In a regression approach, the severity level is treated as a continuous variable, and the objective is to predict a numerical value representing the severity. This entails preparing a dataset with features related to the disease, selecting relevant predictors, choosing a suitable regression model (e.g., linear regression or decision tree regression), training the model on the dataset, evaluating its performance, and subsequently using it to predict severity scores for new data.

On the other hand, a classification approach treats severity levels as distinct classes, with the goal of assigning instances to predefined severity classes (e.g., low, medium, high). Similar to the regression approach, data preparation involves collecting a dataset with relevant features, but now the severity level is categorized. Feature selection, model selection (e.g., logistic regression, decision tree classifiers, or neural networks), training, evaluation, and prediction steps follow, but the focus is on classifying instances into predefined severity classes.

Key considerations include threshold selection in the classification approach, where a decision must be made about severity class assignments based on a chosen threshold. Both approaches require high-quality, well-annotated data that accurately represents the problem at hand. The choice between regression and classification hinges on the nature of the severity variable and the specific goals of the analysis, with each approach offering unique advantages depending on the problem's characteristics. Figure 2 shows the end to end system framework.

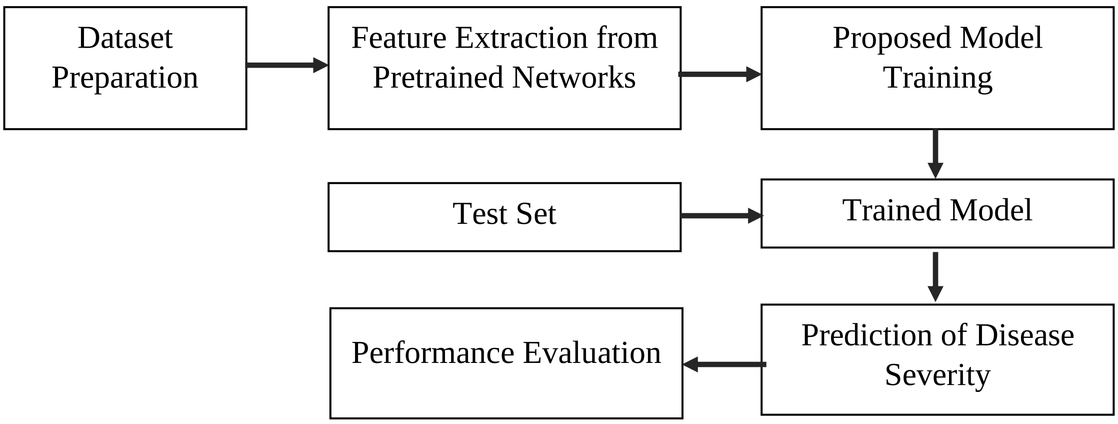

Fig 2: End to end system framework

3.1 Dataset Preparation

The dataset [19] consists of northern leaf disease images of Maize crop. The image count details are shown in table 1. The original dataset is divided in five stages in which stage 1 is mild level of disease and 5th stage is severe stage.

Table 1: Severity work dataset details

Disease Level	% Disease Severity	Image Count	Augmented Count
1	1-20	108	432
2	21-40	330	1320
3	31-60	297	1188
4	61-80	231	924
5	80 above	111	444
		Total	4308

3.2 Feature extraction

3.2.1 Features from Pretrained Network

When using ResNet101 [20] and Inception-V3 [21] for feature extraction in leaf disease classification, optimal layer selection is crucial. For ResNet101, starting at the last layer in the final residual block is strategic. Considering all sublayers, ResNet101 has a total of 347 layers. In Inception-V3, selecting a deeper layer close to the network's end is suitable for capturing abstract features. The precise layer number varies based on implementation. After extracting features from both networks, concatenation precedes passing through an attention layer. This layer selectively assigns weights to features, with attention mechanisms like channel-wise or spatial attention tailored to task requirements. Subsequently, the features enter one or more dense layers, the architecture of which is customized for the specific task and dataset.

3.2.3 Proposed Architecture

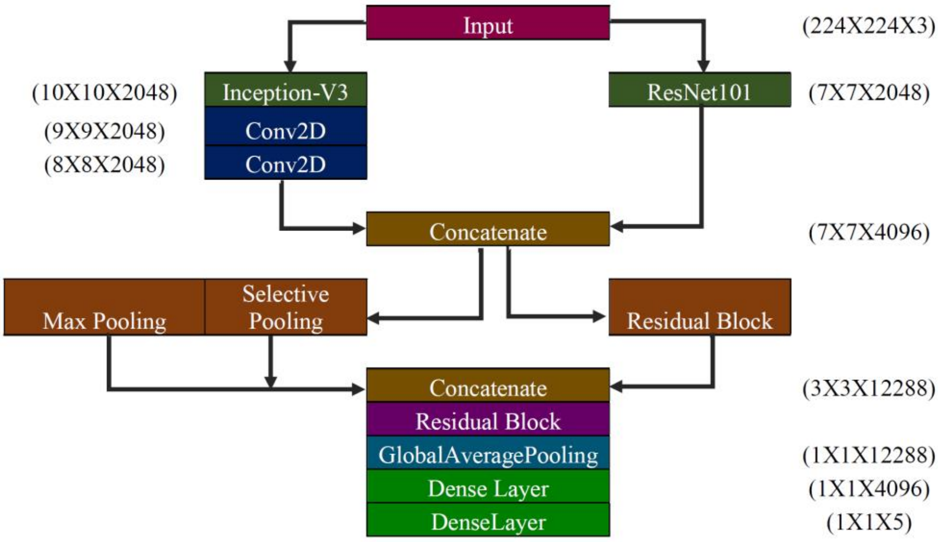

Fig 3: Architecture Proposed Model

In the proposed model architecture as shown in figure 3, the model starts with a (224x224x3) input layer. Using ResNet101 and Inception-V3, it extracts (7x7x2048) and (10x10x2048) feature maps. These maps, from the last selected layer before GlobalAveragePooling, are matched, concatenated, and enhanced through an attention layer. Combining this with the Residual Pooling block output, followed by an additional residual block, features reach the GlobalAveragePooling layer. The output enters a Dense layer with 256 ReLU-activated neurons, and the final Dense layer uses Softmax for eight-class classification.

$$ResNet101_{output} = ResNet101(InputImage) \quad ...(1)$$

Where dimensions (224x224x3) are set for the Input_Image.

$$Inception_{output} = Xception(InputImage)$$

...(2)

$$Inception_{output\_Conv} = Conv2D(Inception_{output})$$

...(3)

Where (10x10x2048) are the output dimensions. Thus combination of features is done by concatenation step,

$$Concatenated_{Featres} = Concatenate(ResNet101_{output}, Inception_{output})$$

...(4)

The combined features obtained are then passed thorugh custom CNN layers as detailed further.

3.2.4 Attention Layer:

The SelectivePooling [22] operation is not merely a feature within neural network architectures; it is a pivotal and indispensable mechanism that significantly contributes to the model's learning and discriminative capacity. This operation, with its capability to compute either the average value or select the maximum value from localized regions within the input feature map, plays a crucial role in extracting meaningful information from the input data.

The intricacies of the SelectivePooling process unfold as a window traverses the input feature map, dynamically calculating the average or identifying the maximum value within each local region. This window, systematically sliding across the entire feature map, captures information at various spatial positions. The elegance of SelectivePooling lies in its versatility, allowing it to seamlessly switch between average and maximum pooling strategies, thereby offering a comprehensive and adaptive approach to information aggregation. SelectivePooling stands as a cornerstone in the advancement of neural network architectures. Its adaptability, derived from the fusion of average and maximum pooling, empowers models with a nuanced understanding of input data, enhancing their discriminative capacity and contributing significantly to their overall efficacy in diverse tasks, ranging from image classification to complex object detection scenarios.

$$Attention_{output} = Concatenated_{Features}.AveragePool(Concatenated_{Features}) + Concatenated_{Features}.SelectPool(Concatenated_{Features})$$

...(5)

4. Results and Discussion

Evaluation of the proposed model is conducted for 5-way severity classification in maize leaf disease detection. The results, as depicted in the table and figure, demonstrate the superiority of the proposed model compared to ResNet101 and Inception-V3, particularly with the incorporation of an attention layer. Table 2 presents the performance metrics utilized for model assessment, providing a comprehensive view of the effectiveness of the proposed approach in severity classification and the 5-way classification task.

Table 2: Performance Parameters

Precision	TP/(TP + FP)
Recall/Sensitivity	TP/(TP + FN)
F1 Score	2*(Recall * Precision) / (Recall + Precision)
Specificity	TN/(TN+FP)
Accuracy	TP + TN / (TP+TN+FP+FN)

A 5-Fold analysis is observed for models stability of training. The performance of the model is seen stable after 4 the fold of training stage. Figure 4 shows performance of 5-Fold Analysis.

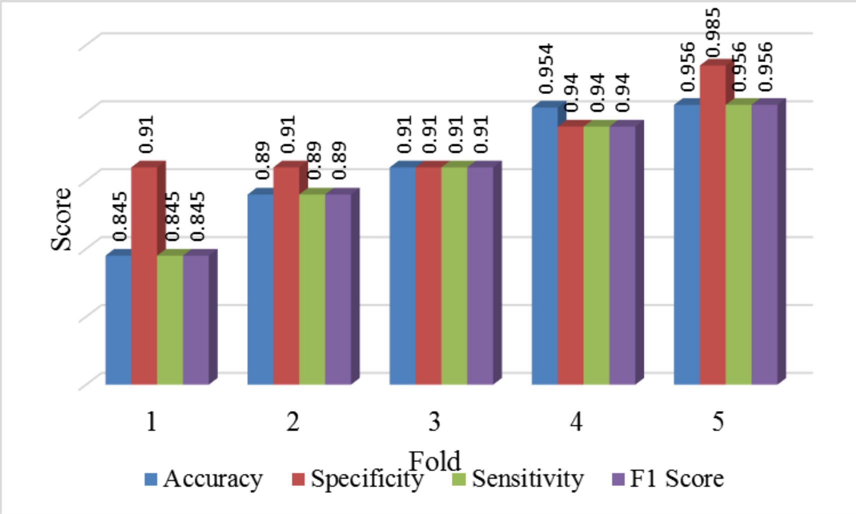

Fig 4: 5-Fold Analysis for Model's Stability

A comparative analysis of standard CNN models by retraining them on maize severity dataset is evaluated. The results are shown in Figure 5. The model's performance with use of proposed model is shown in figure. The results showcase the performance of various models in a classification task, with metrics such as accuracy, specificity, sensitivity, and F1 score providing a comprehensive evaluation. The VGG16 and VGG19 models demonstrate strong accuracy at 0.82 and 0.84, respectively, with balanced specificity and sensitivity. ResNet50 and ResNet101 exhibit improved accuracy at 0.845 and 0.89, showcasing robust performance. Inception-V3 and MobileNet-V2 surpass previous models with higher accuracy, reaching 0.91 and 0.92, respectively. The proposed model outshines all others, achieving remarkable accuracy at 0.956, accompanied by high specificity, sensitivity, and F1 score, indicating its efficacy and potential for practical applications in the classification task.

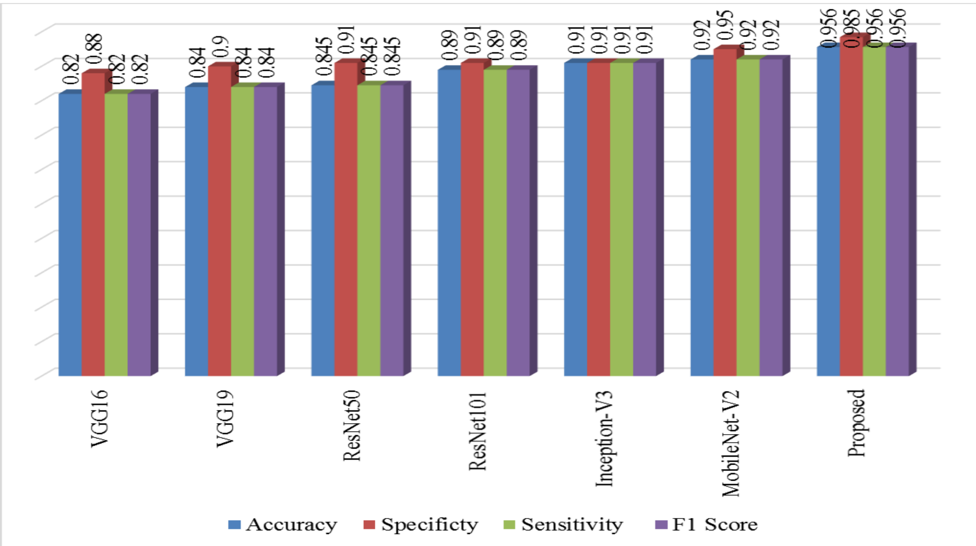

Fig 5: Performance Comparative Analysis of Severity Prediction

In disease severity classification, a confusion matrix serves as a critical evaluation tool, offering a detailed breakdown of a model's performance. The confusion matrix analysis is shown in figure 6. It goes beyond accuracy metrics, providing insights into the model's ability to correctly classify different severity levels. By quantifying true positives, true negatives, false positives, and false negatives, the confusion matrix identifies specific areas of strength and weakness in the model. Metrics such as sensitivity, specificity, precision, and negative predictive value help assess the model's accuracy in identifying severe and non-severe cases. Moreover, the matrix aids in optimizing decision thresholds and communicating model performance to healthcare professionals.

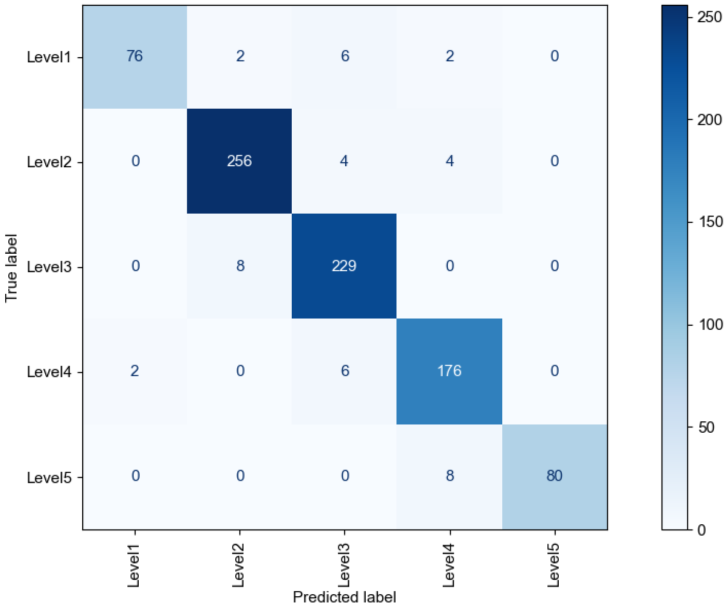

Fig 6: Confusion Matrix Analysis for Proposed Method.

Discussion:

In the collaborative utilization of ResNet101 and Inception-V3 for feature extraction, the critical task of determining the optimal layer from each network emerges as pivotal for effectively extracting features that complement and distinguish. The selection of layers is contingent on the specific characteristics of the task and dataset. In the context of leaf disease classification, an efficient starting point for ResNet101 may involve extracting features from the last layer within the final residual block, just preceding the global average pooling layer. Taking into account all sublayers within the Residual Block, ResNet101 comprises a total of 347 layers. Conversely, for Inception-V3, a strategic starting point may involve extracting features from a specific layer. The selection of an appropriate layer in Inception-V3 entails considering deeper layers closer to the end of the network, renowned for capturing more abstract and high-level features. Subsequent to the extraction of features from ResNet101 and Inception-V3, these features can be concatenated and channeled through an attention layer. The attention layer assumes a central role in selectively assigning importance to various features based on their relevance to the classification task. This systematic approach results in the proposed model outperforming other standard models, boasting an accuracy of 0.956, specificity of 0.985, sensitivity of 0.956, and an F1-Score of 0.956. The noteworthy specificity value of 0.985 underscores the model's adeptness in disease severity classification, emphasizing its ability to discern between different severity levels, a crucial capability in scenarios where precise identification of non-severe cases holds significant importance.

5. Conclusion

The research delves into the pressing issue of maize crop disease severity estimation through the application of advanced machine learning methodologies. The significance of this endeavor lies in its implications for global food security and agricultural economies. By leveraging Convolutional Neural Networks (CNNs), specifically employing ResNet101 and Inception-V3 architectures, the study aims to automate the classification of maize leaf diseases, offering a robust alternative to labor-intensive manual feature extraction. The study highlights critical stages in CNN model development, hyperparameter tuning, and model training and evaluation. Diverse and accurately annotated datasets form the cornerstone of model precision and reliability. The incorporation of pre-trained ResNet101 and Inception-V3 models, trained on extensive image datasets like ImageNet, enhances feature extraction capabilities for more nuanced disease diagnosis. Significantly, the study addresses disease severity estimation, extending beyond mere classification. The identification and analysis of essential features such as lesion size, color changes, texture variations, and spatial distribution play a pivotal role in both disease detection and accurate severity level estimation. The proposed model integrates an attention layer and ResidualBlocks to refine feature representation, resulting in a more nuanced and context-aware severity assessment. Empirical results underscore the effectiveness of the proposed model, outperforming established architectures like ResNet101 and demonstrating superiority in accuracy, specificity, sensitivity, and F1 score. The achieved specificity of 0.985 is particularly notable, signifying the model's exceptional accuracy in discerning non-severe cases.

The research contributes to advancing automated disease detection in maize crops and pioneering a nuanced approach to severity estimation. By combining state-of-the-art CNN architectures with meticulous feature analysis, the study presents a comprehensive solution poised to impact agricultural practices, enhance crop productivity, and contribute to global food security efforts. Navigating the intersection of technology and agriculture, the research demonstrates the transformative potential of machine learning in addressing real-world challenges and fostering sustainable agricultural practices.

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