Journal of Theoretical and Applied Information Technology
31st May 2024. Vol.102. No. 10

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ARTIFICIAL INTELLIGENCE FRAMEWORK FOR MULTI-CLASS SUGARCANE LEAF DISEASES CLASSIFICATION USING DEEP LEARNING ALGORITHMS

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ABSTRACT

Sugarcane is a crucial crop in the global agriculture industry, contributing significantly to the production of sugar, ethanol, and other by-products. However, the prevalence of various diseases can severely affect sugarcane yield and quality, making timely and accurate disease detection imperative. Current methods for sugarcane disease detection predominantly rely on traditional image classification models, which often lack the required precision and efficiency, leading to delayed interventions and compromised crop health. To address these limitations, this paper introduces an efficient and novel comparison of Efficient deep learning models that leverages the strengths of multiple deep learning classifiers, including Alex net, ResNet18, VGG19, and Densenet201, for enhanced sugarcane disease prediction. These diseases include Red Rot, Red Rust, mosaic, and yellow leaf disease. In our approach, individual classifiers are initially employed to classify sugarcane images, followed by the identification and comparison of the best-performing classifiers. In this paper, we have used 1990 sugarcane leaf images for the classification of leaf diseases into normal, red rust, red rot, and bacterial blight. or four class classifications, VGG19 had the greatest accuracy of 98.82%, precision of 96.77%, and sensitivity of 96.33%. The implications of this work are profound, as the proposed model significantly outperforms existing methods in terms of efficiency, accuracy, and timeliness. This advancement holds the potential to revolutionize sugarcane disease detection, ultimately contributing to better crop management, improved yields, and enhanced profitability for farmers and stakeholders in the sugarcane industry. The integration of efficient deep learning models in agriculture paves the way for more informed decision-making processes, ultimately safeguarding the livelihoods of those dependent on sugarcane farming.

Keywords: *CNN, Mosaic, Red Rot, Yellow, Red Rust*

1. INTRODUCTION

Sugarcane is a vital crop that plays a significant role in the global agricultural economy, contributing to the production of sugar, ethanol, and various other by-products. However, the prevalence of numerous diseases can significantly impact sugarcane yield and quality, posing a serious threat to farmers and stakeholders in the sugarcane industry. Timely and accurate disease detection is therefore essential for effective

Disease management and mitigation. Before moving to further details in this research, here are some important definitions. Deep learning is an extension to machine learning where models are based on neural networks. Artificial Intelligence (AI) is the technology that includes machine

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

learning and deep learning techniques. Traditional methods for disease detection, which largely rely on visual inspection, are often subjective, labor-intensive, and inefficient. With the advent of machine learning and deep learning technologies, image based disease detection has emerged as a promising alternative. Various deep learning models, such as convolution neural networks (CNNs), have been successfully employed for image classification tasks, including disease detection in crops. However, these models are not without their limitations, as they often require large amounts of labeled data and computational resources, and may not always provide the desired level of accuracy and efficiency [1, 2, 3].

Sugarcane is a crop that contains a high concentration of sucrose, a kind of sugar. It may be used to make jaggery, white sugar, and a variety of byproducts like as bagasse and molasses. Sugarcane is used to create 75% of the world's sugar. India is the world's second-largest producer and user of sugar. India also boasts the world's secondlargest agriculture-based sector citekhan2017image. Sugarcane juice is naturally alkaline, thus drinking it can help prevent breast and prostate cancer. It is also beneficial to the healthy working of the liver and kidneys, as well as maintaining appropriate blood pressure levels. However, disease outbreaks in the sugarcane plant have resulted in crop damage [4]. Infected sugarcane seriously reduces crop output. For efficient agricultural production, it's critical to keep an eye on people's health and disease. Image processing and deep learning (DL) are used to diagnose ill stems, leaves, coloured fruits, unhealthy sizes, shapes, and areas of leaves, among other things [5]. Because sugarcane takes longer (10–16 months) to develop, diseases can easily infect it. For instance, the sugarcane plant is susceptible to a number of illnesses brought on by bacteria, fungi, viruses, phytoplasma, or protozoans. There are only a few mosaic diseases that affect sugarcane, including red rot, bacterial blight, and rust.

In order to address the growing problems in farms and agricultural settings brought on by climate change as well as a lack of information and resources, professionals, farmers, and decision-makers are becoming more interested in applying machine learning. Earlier works have demonstrated the use of machine learning for challenging agricultural tasks as crop characterization, crop health monitoring, soil monitoring, disease diagnosis, and grading [6]. Machine learning is used with sensors, drones, GPS, and other technologies in addition to others [7]. It thereby assists farmers in ensuring profitability, maximizing crop health, and raising agricultural output.

Recently, deep learning has been used to classify a variety of illnesses. Diseases are the main source of crop losses in terms of quantity and quality [8]. There are presently few machine learning-based approaches for classifying illnesses, though. The effects of disease epidemics on livelihood and food security might vary. As a result, accurate disease detection and classification are needed to support both experienced and beginning farmers. Advancements in deep learning now open the way to better disease classification while addressing the requirement for early disease detection to protect crops in time, as cited in the [9].

In this paper, we propose a novel Efficient deep learning model for enhanced sugarcane disease detection. Our approach combines the strengths of multiple deep learning classifiers, including VGGNet19, ResNet18,alexnet, and densenet201, to improve the precision, accuracy, and efficiency of sugarcane disease prediction. By fusing the best performing classifiers, we aim to create a robust model that leverages the complementary strengths of each individual classifier, thereby overcoming the limitations of single-model approaches. The proposed Efficient model is rigorously evaluated using a comprehensive dataset of sugarcane images, and the results demonstrate its superiority over existing methods in terms of accuracy, precision, recall, AUC, and specificity. Moreover, our model significantly reduces the delay in disease detection, ensuring timely interventions and improved crop health. This work holds great potential to revolutionize sugarcane disease detection, ultimately contributing to better crop management, higher yields, and increased profitability for farmers and stakeholders in the sugarcane industry scenarios.

Motivation: Sugarcane diseases pose a significant threat to global agriculture, with the potential to cause substantial yield losses and economic damage. Traditional methods for disease detection, such as visual inspection, are often inaccurate and time-consuming, leading to delayed intervention and further spread of the disease. With the rapid advancements in machine learning and deep learning technologies, there is a growing interest in leveraging these tools for efficient and accurate disease detection. While various deep learning models have been

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

employed for image-based disease detection in crops, there is still a need for models that can provide higher accuracy, precision, and efficiency, particularly in the case of sugarcane diseases. This motivated us to develop a novel Efficient deep learning model that combines the strengths of multiple deep learning classifiers to enhance the performance of sugarcane disease prediction.

Sugarcane is recognised as a commodity both in the Philippines and across the rest of the world. In the Harmonised National Research and Development Agenda 2022 [10], the Department of Science and Technology (DOST) has prioritised sugarcane. In 2017, the sugarcane industry in the Philippines produced more than 70 billion pesos, according to [11]. Despite the fact that many industries rely on sugarcane and the goods it produces, disease and insect infestation are having an impact on sugarcane production due to rising environmental concerns and climate change. The Philippines also lacks expertise and research about the development of sugarcane. It was thus selected as one of the crops for the DOST research programme. However, only a small number of deep learning-based methods may be used locally for early sickness classification and detection. The main contributions of the work are

- We have used four pre-trained CNNs for the classification and also suggesting which model classify the leaf diseases efficiently.
- We have done both four class classification.
- We have used the hyper-parameters to tune the network models.
- We have calculated ten performance evaluation metrics.

This paper has the following structure: Related and literature review is discussed in section 2. Information about the data set is provided in Section 3. The proposed methodology for classification of sugarcane leaf diseases is outlined in Section 4. Model results and discussions are described in Section 5. Section 6 discusses significance of our work and its limitations while the models' final conclusion is presented in Section 6.

2. RELATED WORK

Sugarcane is one of the most important crops in the global agriculture sector, providing essential raw materials for sugar and ethanol production. However, the cultivation of sugarcane is often threatened by various diseases that can significantly impact yield and quality. The timely and accurate detection of these diseases is crucial for effective management and mitigation.

Traditional methods [12, 13, 14] for disease detection in sugarcane primarily involve visual inspection, which is highly labor-intensive, subjective, and often inaccurate. In recent years, there has been a growing interest in leveraging machine learning and deep learning technologies for image-based disease detection in crops, with numerous studies demonstrating the potential of these tools in agricultural scenarios. Convolutional Neural Networks (CNNs) have emerged as one of the most popular deep learning models for image classification tasks, including disease detection in crops [15, 16, 17]. Several studies have employed CNNs for the detection of diseases in sugarcane. For instance, [18, 19, 20] utilized a CNN model for the classification of sugarcane diseases and reported an accuracy of 90%. Similarly, [21, 22] employed a CNN-based model for the detection of yellow rust disease in wheat and achieved an accuracy of 96.7While these studies highlight the potential of CNNs in disease detection, there are still several limitations associated with single-model approaches [23, 24, 25]. One of the main challenges is the requirement for large amounts of labeled data and computational resources. Furthermore, single-model approaches may not always provide the desired level of accuracy and efficiency, particularly in the case of complex and diverse datasets [26, 27]. To overcome these limitations, Efficient learning has emerged as a promising alternative. Efficient learning [28] involves the combination of multiple models to improve the overall performance of the system. There have been several studies that have explored the use of Efficient learning for disease detection in crops. For example, [29, 30, 22] proposed an Efficient model that combined multiple machine learning algorithms for the detection of plant diseases and reported an improvement in accuracy compared to single-model approaches.

Depending solely on the illness's severity, crop loss due to disease may range from 10% to 50% [31]. Accurate and prompt diagnosis will undoubtedly decrease crop loss in sugar beet fields.

Thus, illness signs must be promptly diagnosed and suitable actions must be done right away to avoid the development or spread of the infections [32]. Precision agriculture and the accuracy of plant protection practises may both be improved and expanded by advances in computer vision [33]. For the purpose of identifying and categorising sugarcane illnesses, numerous research presented the method known as image processing. The feature was extracted from an image using an image processing approach, and its infection status was then determined [34]. By the use of direct image processing, it is feasible to analyse the colour and form characteristics of diseased leaf pictures in order to identify the infected regions and classify the disease's severity. Instead, the support vector machine (SVM) and K-means clustering were used to categorise diseases using machine learning (ML) techniques. Similarly, convolutional neural networks(CNN) and artificial neural networks (ANN) were used in the illness classification process using deep learning (DL) techniques. The use of DL methods for plant pest and disease detection has received much research in recent years [35]. Even though a number of methods and strategies have been developed, there is still potential for development [36].

To achieve the highest accuracy rate in identifying and diagnosing illnesses, Militante and Gerardo [29] sought to combine several CNN frameworks of DL methods. A maximum accuracy rate of 95.40% was achieved by the model, which was trained to identify illnesses using 14,725 images of sugarcane leaves infected with disease and healthy sugarcane leaves. LeNet, VGGNet, and StridedNet are components of the CNN architecture, and they have been used to recognise and identify illnesses. A portable device that uses SVM to identify the yellow spot disease on sugarcane leaves was created by Padilla et al. [37]. The work focuses on creating a model that, using image processing, records and displays pictures of sugarcane leaves integrated with a single unit system. By recognizing a yellow spot on the leaf, the researcher trained the model for describing and categorizing the variation among leaves that are healthy or unhealthy. A DL-NN framework was provided by Hemalatha et al. [38] in which the various agricultural diseases are predicted by training the system on a picture of a diseased leaf. The following diseases are distinguished: helmanthospura leaf spot, Cercospora leaf spot, red rot, and yellow leaf disease. A CNN that has been trained for image classification is used in the procedure. By changing a CNN parameter, Ozguven et al. [39] created an improved Fast RCNN framework, and they have since published Fast RCNN architectures for automatically identifying the sugar beet leaf disease. By using image processing techniques, Thilagavathi et al. [40] concentrated on recognising the various illnesses in a sugarcane leaf and created a web application for the farmer to discern the major diseases of sugarcane [40]. The plan captures the leaf picture and applies adoptive histogram equalisation (AHE), followed by segmentation using the k-means clustering technique. The statistical properties, including skewness, variance, mean, covariance, and standard deviation, are retrieved using PCA and GLCM. Finally, SVM is used to do the classification and detection. For the sugarcane white leaf (SCWL), Quoc et al. developed a loop-mediated isothermal amplification (LAMP) as an alternative approach for the effective and speedy detection of the SCWL phytoplasma within thirty minutes [41]. The 16SrXI SCWL phytoplasma has been detected using the three LAMP primer sets. The control was the plant cytochrome oxidase (cox) LAMP prime, which enhances a planthousekeeping gene. For monitoring the two sugarcane field experiments with nitrogen (N) fertiliser input from the wet tropic area of Australia, Shendryk et al. used a UAV mounted LiDAR and multi spectral image sensor [42]. We examined crop output in terms of vegetation, height, and density indices from the six experiments that were applied at forty-two-day intervals. Reverse transcription LAMP (RT-LAMP) for SCSMV diagnosis was created by Wang et al. [43]. Four SCSMV primers, including P2-F3, P2-B3, P2-FIP, and P2-BIP, have been screened and designed through a panel of sugarcane viruses in accordance with the conserved polyprotein gene nucleotide sequences of SCSMV isolated that differed from sorghum mosaic virus (SrMV) and sugarcane mosaic virus (SCMV). Dhaka et al. [44] used deep CNN to conduct a thorough study on plant leaf diseases in 2021. Plant leaf diseases are categorised using common techniques such picture flipping, scaling, cropping, translation, and the addition of Gaussian noise. The benefit of this work is that it offers a very thorough overview of plant leaf diseases, which is highly helpful for researchers; nevertheless, the work's main disadvantage is that it mostly employs basic conventional

Journal of Theoretical and Applied Information Technology
31st May 2024. Vol.102. No. 10

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

procedures and little DL approaches. For the detection of cassava disease, Olusola Oluwakemi Abayomi-Alli et al.[45] discovered a more effective method. It makes use of the colour transformation approach for picture preparation. This study has the advantage of successfully classifying photos using the augmentation approach, but it has the disadvantage of having poor illness detection accuracy. Almadhor et al. [46] implemented the project in 2021 to use machine learning methods to identify illnesses of guava plants. This initiative offers precise disease identification findings for guava plants. This work needs to be expanded using contemporary DL or ML approaches. With the MASK RCNN approach, Rehman et al. [47] created a framework to identify apple leaf diseases. Region-based convolutional neural network, or RCNN, is used here. For the purpose of identifying illnesses of apple leaves, this model provides effective results. The requirement to train the many photos is the problem in this endeavour.

The aforementioned known research all focus on disease detection in sugarcane leaves using different strategies. The available current efforts were geographically dispersed, of limited scale, and of little use in correctly diagnosing and classifying the diseases of sugarcane leaves. Deterministic detection and classification methods are thus needed for the recommended study activity. The main objective of the proposed study is a more precise diagnosis and classification of sugarcane leaf diseases.

3. DATASETS

In this, we have collected two different datasets that are publically available in kaggle [48, 49]. This [48] dataset contains the three classes of sugarcane diseases such as bacterial blight, smuts, red rust where as [49] consists of three classes such as red rot, red rust, and smuts images. In this work, we combined these two works for two different scenarios such as four classes red rust, red rot, mosaic, and yellow leaf condition classes and for binary classification; normal and abnormal classes. This combined dataset consists of 1990 images, all are in .jpg, .png, .jpeg format. The sample images are shown in the figure 1. This dataset has 462 mosaic, 518 red rot, 514 red rust, and 505yellow leaf diseasesugarcane leaf images. All these images are resized to fit the input of CNN All these images are pre-processed and denoised that are used in our previous work of sugarcane classification into diseased and normal images. Then images are divided into 60% for training and 40% for testing and validation.

Table 1: Datasets used for the Classification

Disease	Train	Test	Total
Mosaic	277	185	462
Red Rot	311	207	518
Red Rust	308	206	514
Yellow	303	202	505
Total	1199	791	1990

Figure 1: Sugarcane Leaf Diseases

4. METHOD

Provided sugar cane leaves, developing a framework with deep learning models for disease detection and classification is the problem considered. The classification of sugarcane leaf diseases from digital leaf images that are publically available in kaggle. The proposed model of classification of sugarcane leaf diseases is shown in the figure 2. In this, images are collected from various databases and given these images are undergone the image pre-processing. In training, each CNN model is trained by using hyper-parameters: 50 epochs, 1e-4 constant learn rate, 32 batch size, validation frequency of 40 and cross entropy regularization with ADAM optimizer.

Table 2: Network Training Options

Function	Value
Optimizer	Adam
Epochs	50
MiniBatchSize	32
Initial Learn Rate	0.0001

Testing of each CNN model is done with test set of images after completion of the training. In testing, images are classified into four classes: mosaic vs. red rot vs. red rust vs. yellow leaf. The steps of classification of the sugarcane diseases are

- Collection Datasets.
- Image pre-processing.
- Data augmentation for training Images.
- Designing CNN model and defining hyper-parameters.
- Train each CNN model.
- Test each CNN model using test sets.
- Repeat steps from 3 if training is not done.
- Calculate the performance metrics.

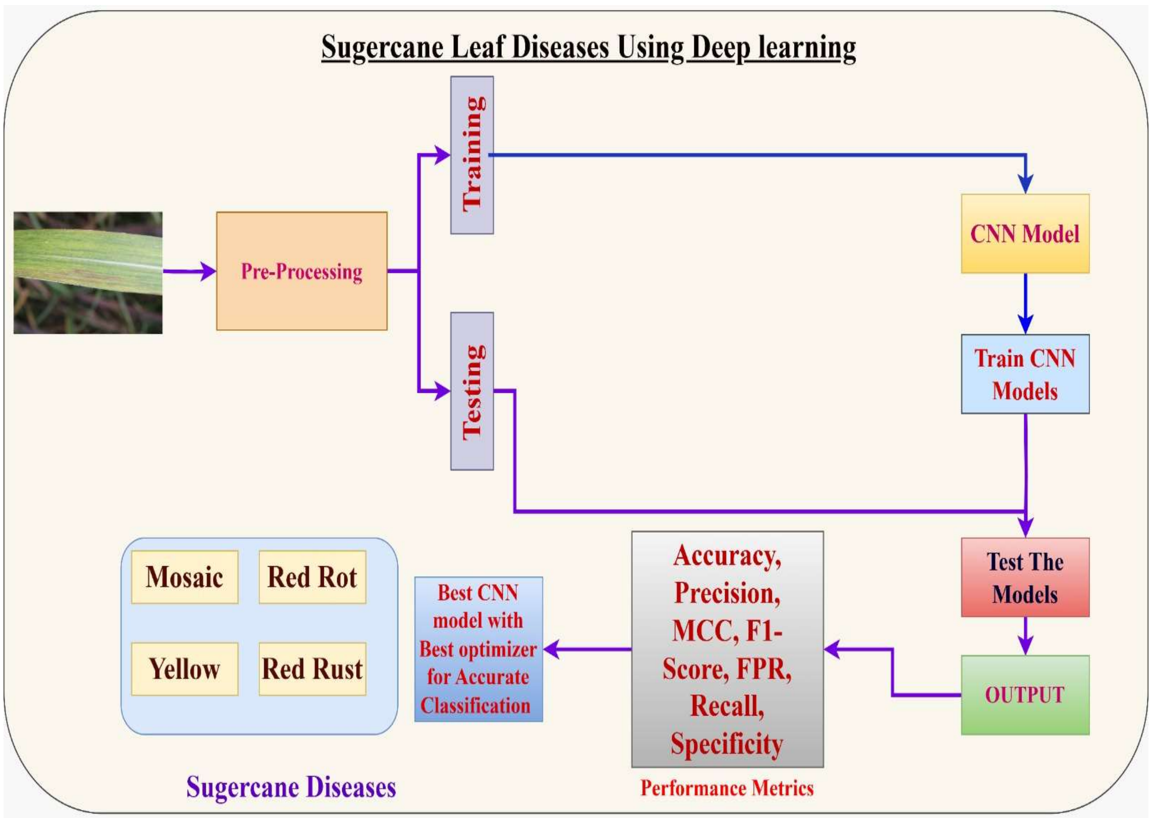
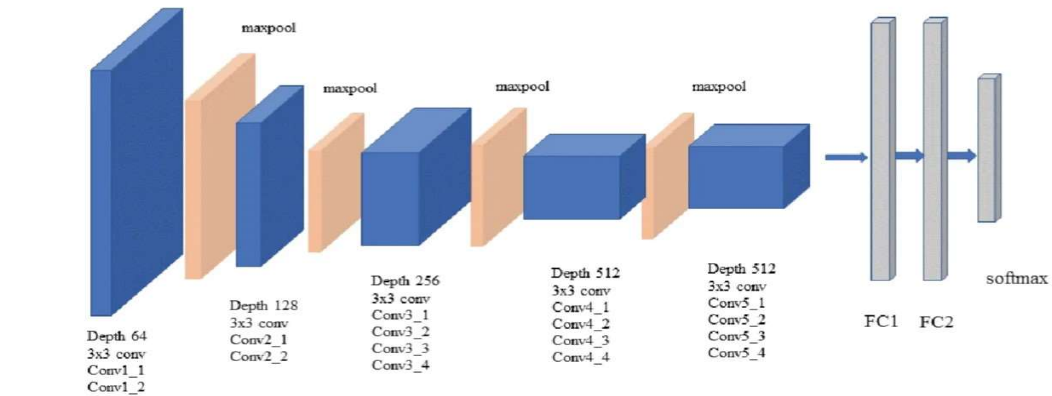


Figure 2: Sugarcane Leaf Disease Classification Model



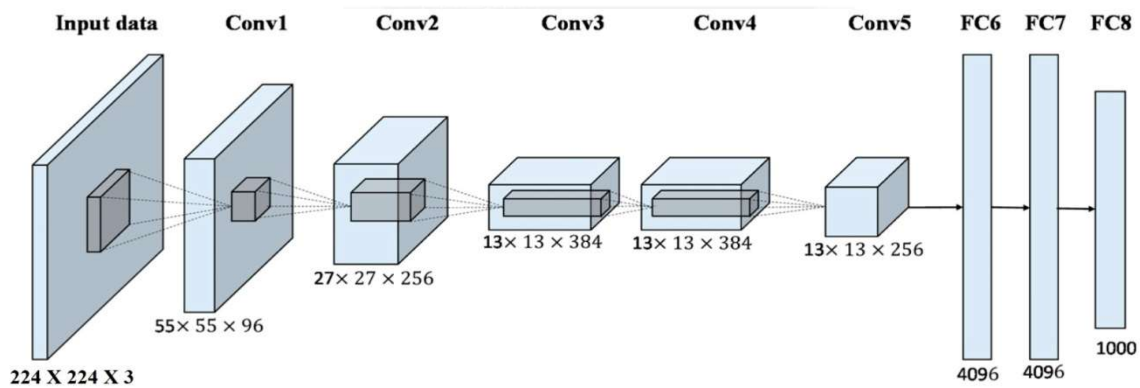


Figure 3: Architecture of Alexnet

Figure 4: Architecture of VGG19

In this, we have used softmax for activation for the multi-class classification. This softmax is defined as:

$$\delta_{smax}(\vec{x}) = P(y = j|x^k) = \frac{e^{x^k}}{\sum_{j=1}^{N} e^{x^k}} \qquad (1)$$

Where, $\vec{x}$ represents is input vector, j=1, 2, 3,..., Nrepresents number classes.

$$\vec{x} = w_1 z_1 + w_2 z_2 + \cdots\cdots + w_N z_N = \sum_{n=1}^{N} w_n z_n + b = w^T z + bs$$
(2)

Where, w is weight matrix and bs is the bias.

The labels used for the classification in the softmax layer are

Labels= {Y, RR, Ru, M} (3)

Where Y represents yellow leaf, RR represents red rot, Ru represents red rust, and M represents the mosaic.

Then, the softmax output labels is represented as:

$$y = [p_c, \mathrm{Y}, \mathrm{RR}, \mathrm{Ru}, \mathrm{M}, p_1, p_2] \qquad (4)$$

Where, p_c is the probability of object present, p_1, p_2 are the probability of particular class. If there is no object present in the softmax activation, then it is represented as null.

$$y = [0,0,0,0,0,0,0] \quad (5)$$

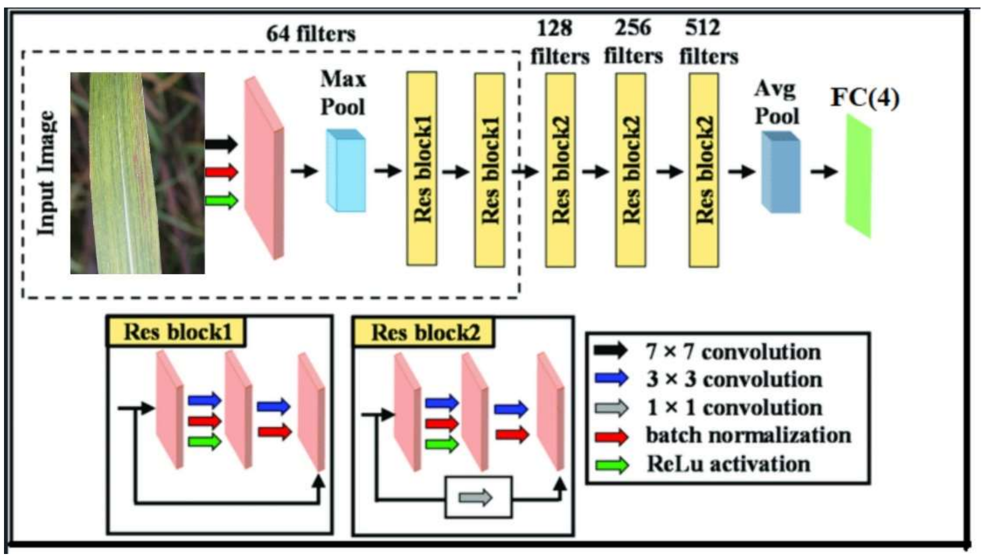


Figure 5: Architecture of Resnet18

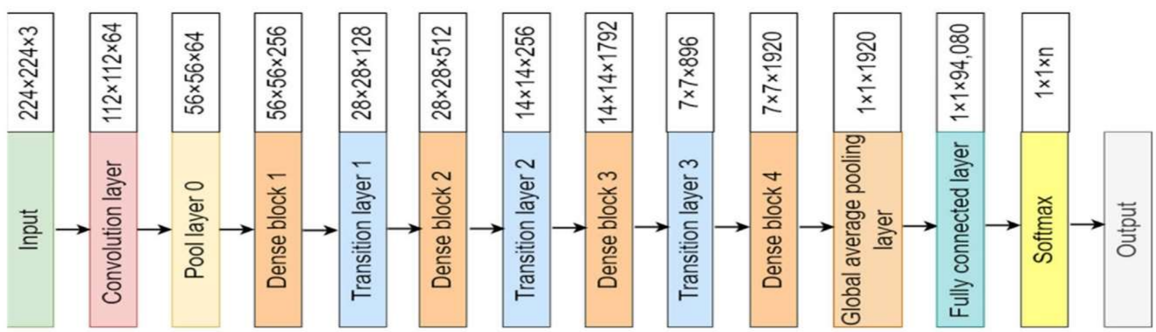


Figure 6: Architecture of Densenet201

In this, we have used binary cross entropy loss and it is given as:

$$B_c = -\frac{1}{N}\left[\sum_{j=1}^{N} k_j \, log(p_j) + (1-k_j) log(1-p_j)\right]] \quad ($$

5. EXPERIMENTAL RESULTS AND DISCUSSION

EXPERIMENTAL RESUL

We have implemented proposed model using Python in 32GB RAM and 1TB SSD with NIVIDIA GTX. In this, we have classified the diseased images into four-class classification. After classification performance evaluation metrics: Accuracy(ACC), Specificity, precision, recall, F-score, Error rate(E_{rate}), false positive rate(FPR),

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Mattew Correlation Co-efficient(MCC) are calculated using the equations from (1) to (8)

$$ACC = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (7)$$

$$Specificitty = \frac{TN}{TN + FP} \quad (8)$$

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

$$F_1 - Score = 2\,X \frac{TP}{2XTP + FP + FN} \quad (11)$$

$$ERate = 1 - ACC \quad (12)$$

$$FPR = 1 - Precision \quad (13)$$

$$MCC = \frac{TP.TN - FP.FN}{\sqrt{(TP + FN)(TP + FP)(TN + FP)(TN + FN)}} \quad (14)$$

Where, TP is true positive, TN is true negative, FP is false positive, and FN is false negative. The accuracy and loss curves shown in the figure 7 Figure 8 shows the confusion matrices of the CNN models that are used for the classification. From these confusion metrics, performance evaluation parameters are calculated and tabulated in the table 3. In this, we have compared the performance of the four pre-trained CNN models. Comparison chart is also shown in the figure 9, 10, 11, 12, and 13.

Table 3: Performance Evaluation Metrics of CNNs

CNN Model	Accuracy(%)	Precision(%)
Alexnet	97.06	94.06
VGG19	98.82	96.77
Resnet18	97.21	90.64
Densenet201	97.94	94.16

6. DISCUSSION

This section discusses about the importance of the proposed work in this paper besides providing its limitations. The proposed system exploits many deep learning models that are CNN based. Each model is a pretrained model which is capable of detecting sugar cane leaf diseases and classify them. These models also support transfer learning to retrain the models as needed. The architecture of each model is different and therefore performance also differs. The models with the proposed deep learning approach could achieve significant performance in leaf disease detection.

6.1 Limitations

The proposed research in this paper could achieve significant results in leaf disease detection. However, the proposed research has certain limitations. The dataset used in this paper for empirical study may not be able to help in generalizing the findings. Another important limitation is that the proposed framework and deep learning models where not subjected to model scaling. Model scaling may help improve efficiency of these models.

7. CONCLUSION

The most important advancements in image classification have been made possible by deep learning, and these advancements have served as the foundation for detecting and treating plant illnesses by leveraging technology to detect images as the basis for recognizing several crop diseases. This comparison technique can effectively categorize sugarcane leaf diseases into Mosaic, red rot, red rust, and Yellow using leaf images. Using weight convolutional neural networks: Alexnet, , VGG19, and Resnet18. The performance of several classifiers in this

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

experimental study's categorization of leaf diseases is compared. Pre-processing and data augmentation techniques improve the accuracy of classification models when the size of the dataset is minimal. For four class classifications, VGG19 had the greatest accuracy of 98.82%, precision of 96.77%, and sensitivity of 96.33%. In the future, the optimization technique may also be utilized to identify the key characteristics from the extraction section in order to improve accuracy.

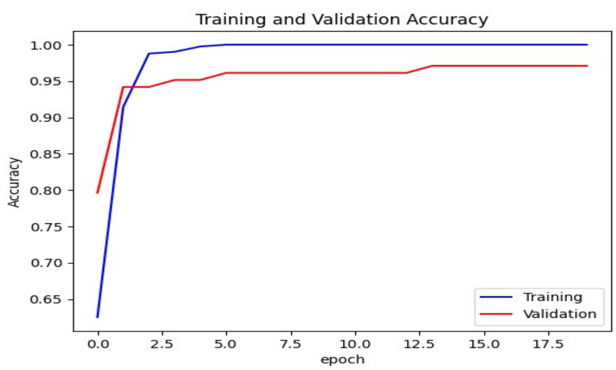
Data Availability

Sugarcane Leaf Disease Dataset 1: https://data.mendeley.com/datasets/9424skmnrk/1

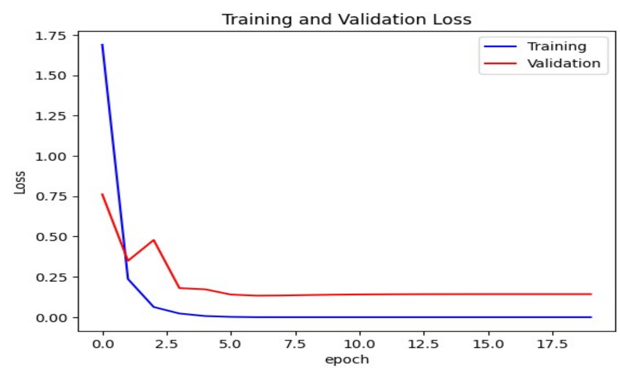
Sugarcane Leaf Disease Dataset 2: https://www.kaggle.com/datasets/pungliyavithika/sugarcane-leaf-disease-classification

Conflict of Interests

There is no conflict of interests.



(a) Accuracy Curve of VGG19



(b) Loss Curve of VGG19

Figure 7: Accuracy and Loss curves of VGG19

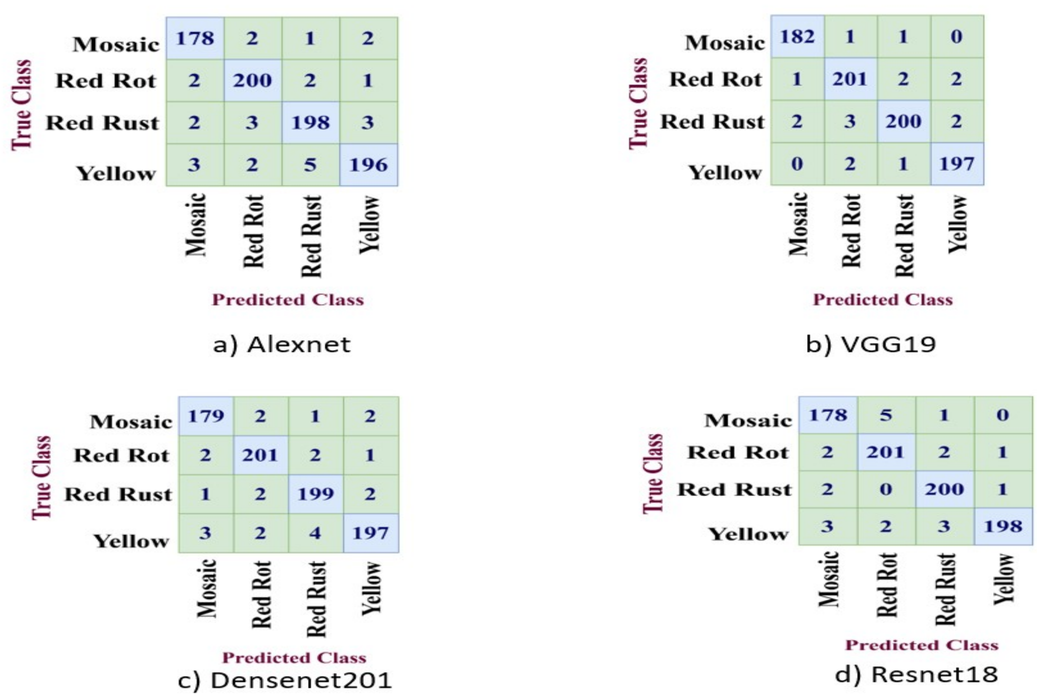


Figure 8: Confusion Matrices

Journal of Theoretical and Applied Information Technology
31st May 2024. Vol.102. No. 10

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

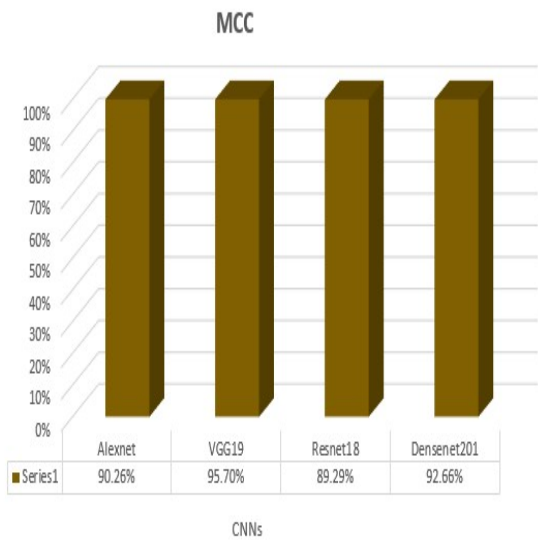


Figure 9: Comparison of the MCC of the CNNs used in Proposed Method

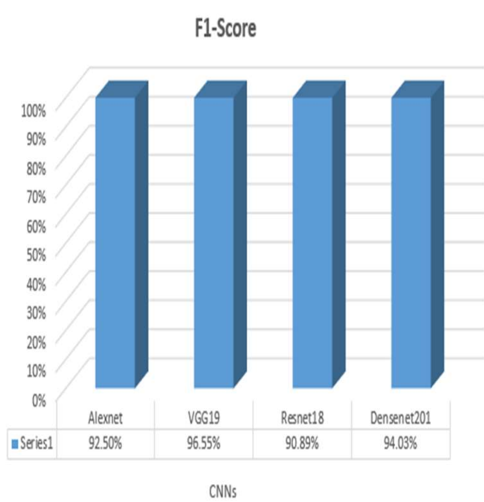


Figure 10: Comparison of the F-score of the CNNs used in Proposed Method

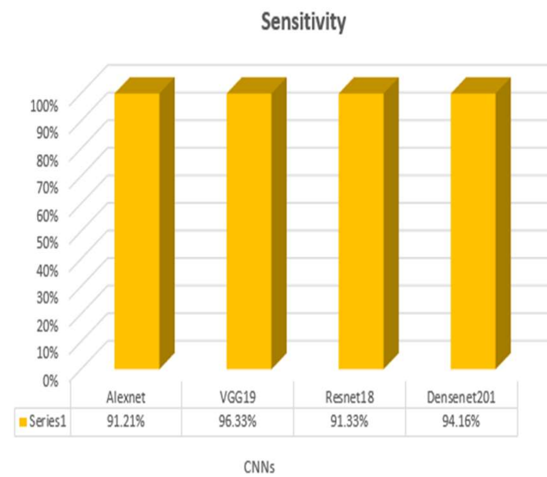


Figure 11: Comparison of the Sensitivity of the CNNs used in Proposed Method

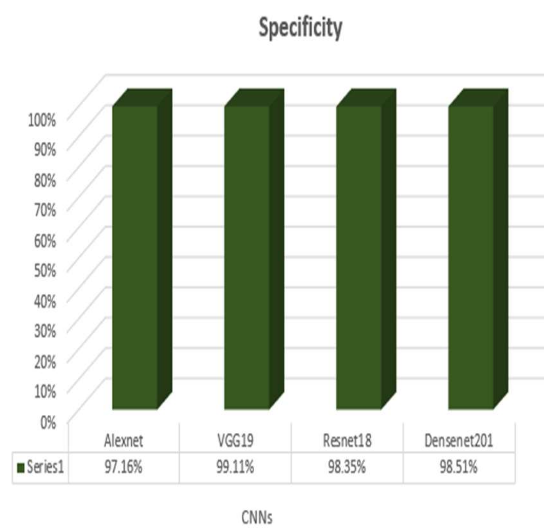


Figure 12: Comparison of the Specificity of the CNNs used in Proposed

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Method

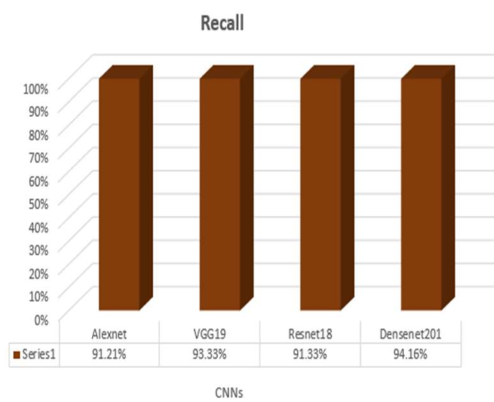


Figure 13: Comparison Of The Recall Of The Cnns Used In Proposedmethod

FUNDING

This work did not receive any external funding.

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