A Novel Approach for Red Rot Disease Detection in Sugarcane Plants Using Transfer Learning Based VGG16 Model

Syed Atir Raza[1] , Nafeesa Yousaf [2]
[1]Department of Computer Science and Information Technology, University of Lahore, 54000, Pakistan
[2]Department of Computer Science, School of Systems and Technology, University of Management and Technology, Lahore Pakistan.
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Abstract

Red rot in sugarcane is a devastating fungal disease caused by Colletotrichum falcat um. It leads to wilting, red discoloration, and yield losses, which can impact sugar production globally. Red rot hampers sugarcane production, causing yield reductions, and economic losses, and affecting the nation's sugar industry demanding stringent disease management strategies. There is a need of a system that detects the red rot disease at an early stage before it spreads. Transfer learning enhances agricultural models, leveraging pre-trained data for improved crop predictions, resource optimization, and sustainability. In this article, we have proposed a transfer learning-based VGG16 model for the detection of red rot disease in sugarcane on a large dataset. The model achieves a remarkable 98.85% accuracy and an F1 score of 0.93 in early red rot detection in sugarcane. This work underscores the potency of leveraging re-trained models for crop disease identification, offering a promising avenue for proactive disease management. This research marks a substantial step towards enhancing crop yield and sustainability, presenting an accessible and impactful technological solution for early disease detection in sugarcane, ultimately benefiting agricultural practices.

Keywords: Smart Agriculture, red rot sugarcane, Deep Learning, Transfer Learning, Machine Learning.

Introduction

Red rot disease in sugarcane[1], caused by the fungus Colletotrichum Falcatum[1], [2], poses a significant threat to global sugarcane production[3]. This destructive pathogen targets the plant's stalk[4], resulting in reddish-brown lesions[1] as shown in Figure 1 and cankers that compromise structural integrity[3]. Infected plants exhibit stunted growth, reduced sucrose content, and ultimately diminished sugar yields. Red rot spreads through contaminated planting materials[5], soil, and water, making it challenging to control[6].

Figure 1. Sugarcane plants affected by Red Rot

Pakistan's sugarcane production is a vital component of its agriculture sector, thriving in the subtropical climates of Punjab province and Sindh Province[7]. The industry characterized by both large commercial farms and small independent growers contributes significantly to the national economy and provided the extensive employment opportunities[7]. However, according to an international report from 2000 to 2022 a loss in sugarcane yield has been observed due to the diseases associated with the sugarcane plant such as red rot, mosaic, rust, yellow leaf as shown in figure 2[8][9]. Red rot is a major and economically significant disease that affects the sugarcane plants badly[10]. Early detection of red rot in sugarcane is crucial. Identifying the initial symptoms promptly enables timely intervention, preventing the spread of disease and minimizing the crop damage. Swift action and strategic fungicide application is key to safeguarding sugarcane crops, ensuring better yields and maintaining overall agricultural sustainability[11].

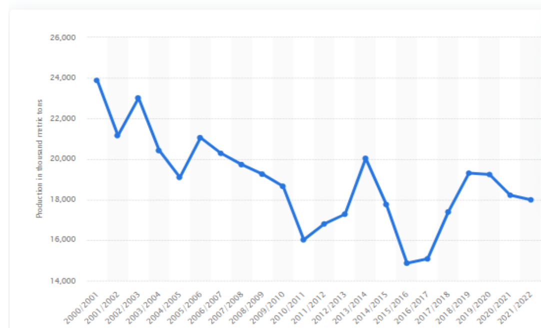

Figure 2. Production of sugar cane in Pakistan 2000 to 2022[8]

In agriculture, the integration of deep learning [12] and transfer learning [13] is revolutionizing the plant disease detection [14]. These advance technologies enhance the accuracy and efficiency of identifying the diseases in the crop, including plants like sugarcane. Deep learning with its neural network architecture, allows for more intricate feature extraction improving diagnostic precision. Transfer learning further optimizes performance by leveraging pre-trained models on large datasets for related tasks [15]. The synergy of these technologies quips farmers with the powerful tools to swiftly and accurately identify diseases, facilitating timely interventions, minimizing the crop losses and promoting the sustainable agricultural practices [16].

In this study, implementing transfer learning with VGG16 model, the research achieves a remarkable 98.85% accuracy and an F1 score of 0.93 in early red rot detection in sugarcane. This work underscores the potency of leveraging

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re-trained models for crop disease identification. The findings emphasize the model's robust performance in accurately identifying the red rot symptoms, offering a promising avenue for proactive disease management. This study provides critical progress in development of a potential technological tool that can be most likely put to actual use for proper and timely detection of diseases pertaining the sugarcane crop, ultimately leading it towards higher productivity levels and better sustenance. Offering a quick and financially sound way to identify disease, this advance could have major implications for agricultural practices as well as improved efficiency across the sugarcane industry.

Organization of this article is as: section 2 is for related work, section 3 is for Materials and Methods, Section 4 is for results and Discussion, Section 5 is for conclusion.

Related Work

V. Tanwar et al. [17] presented a Convolutional Neural Network (CNN) inspired model for detecting red rot disease in sugarcane with 93% accuracy. Although this marks a significant upgrade to the state of art, it still is not good enough when positioned with respect ot our model. Tanwar et al. performance metrics ' s model, which also shown the acceptable accuracy and robustness may need to perform more optimization in addition to some validation works in future for its practical use across different agricultural settings.

Mostafizur et al. [18] has used a YOLO based model to detect the sugarcane diseases with an accuracy of 96.6%. However, work by them had nothing to do with red rot disease which is an important stress in sugarcane cultivation. Moreover, although the model just performed well in all those common cases and not for any other type of disease as they were hoped. This limitation highlighted further needs to improve and test the model for greater generalizability across sugarcane diseases.

Manavalan, R. et al[19]. In view of the rapid diagnosis and information discussed for sugarcane disease, various machine learning techniques associated with Image processing are assessed in state-of-the-art. This report will review their work and explore the potential of these technologies to increase both quality and trust in food safety by speeding up disease detection for agricultural use. But the researchers caution that their study is survey-based and lacks experimental validation of said techniques This lack of empirical verification may restrain the direct applicability of their findings to actual systemic conditions.

Salgadoe et al.[20] pioneers the use of machine learning on UAV multispectral images for white leaf disease detection in sugarcane, showcasing potential advancements in precision agriculture and disease monitoring. However, potential limitations may arise from the dependency on accurate image acquisition conditions, and generalizability maybe affected by variations in environmental factors and diverse field conditions.

Mohd et al. [21] presented a new deep learning approach in detecting sugarcane diseases, demonstrated the potential improvement of detection accuracy and efficiency applicable to multiple agricultural protocols. Nevertheless, these may be accompanied by challenges about the interpretability of models as well as data accessibility and a high computational cost that prevent an immediate practical use of our framework in some contexts.

Prakruthi et al.[22] contributes by applying deep learning techniques to effectively detect sugarcane leaf diseases, demonstrating the potential for accurate and automated disease identification in agricultural settings. However, limitations may arise from the need for large labeled datasets and model performance might be influences by variations in environmental conditions potentially in impacting real-world applicability.

Sujithra et al. [23] Does Performance Analysis of a D-Neural Network for Banana and Sugarcane Plant Leaf Disease Classification: An Effective Insight on the Efficiency of These Networks. Nonetheless, possible drawbacks include a lack of robustness to hyperparameter tuning and reduced generalizability with different datasets or disease severity impairing the model performance in more diverse agricultural settings.

Materials and Methods

3.1 – Dataset

The dataset utilized in this study was sourced from Mendely data repository and focused on red ro disease in sugarcane plants[24] and also we have collected some data from Shakargarh city in Punjab Pakistan, 32°15'43"N 75°09'15"E of such sugarcane leaves affected by red rot. The dataset consisted of 2000 high resolution images, comprising 900 images for training and 1100 images for testing. The dataset contains multiple images that display different types of red rot on sugarcane plants. These images offer a diverse representation of the disease across various sugarcane fields and environmental conditions. The goal of this comprehensive dataset is to train and evaluate the model on a wide range of red rot instances, which will enhance its ability to identify fungal diseases in sugarcane leaves more effectively.

Preprocessing

Prior to model training, a crucial preprocessing phase was implemented on the red rot sugarcane dataset. The image, initially of varying dimensions, were resized uniformly 64 x 64 pixels, optimizing computational efficiency. To enhance model generalization and mitigate overfitting, data augmentation techniques were applied. This involved randomly rotating and flipping images, augmenting the dataset with various to expose the model to diverse perspectives of red rot of sugarcane. These preprocessing steps not only standardized the input size but also facilitated robust model training by introducing variations, ensuring the model’s adaptability to different orientations and scales in the detection of red rot on sugarcane leaves.

Figure 3. Dataset collection location 32°15'43"N 75°09'15"E

Model Architecture

With a focus on transfer learning using the VGG16 architecture, a Convolutional Neural Network (CNN) was used in the model architecture for the detection of red rot in cashew leaves. Using big datasets and pre-trained models to improve the learning of features pertinent to the target task in this case, red rot identification is known as transfer learning. Because it can extract complex hierarchical features, the base VGG16 model which is well-known for its deep architecture and performance in image classification task was used. To improve its comprehension of common visual patterns, the model was pre-trained on a variety of datasets, including ImageNet, before being initialized with weights. To optimize the model for binary classification and differentiate between cashew leaves infected with red rot and those that are not, a customized output layer was incorporated. This layer made it easier for the model to anticipate details unique to each manifestation of anthracnose.

VGG16's convolutional layers were essential to the process of extracting features. These layers were in charge of identifying features specific to areas impacted by red rot, such as edges, textures, and forms. The significant features were captured by further down sampling the spatial dimensions using max-pooling layers. Dropout layers were purposefully added during training to reduce overfitting and improve model generalization by arbitrarily deactivating a portion of neurons. The model's capacity to generalize outside of the training set was enhanced by this regularization method. The final model architecture showed how transfer learning concepts may be seamlessly integrated with task-specific fine-tuning and the knowledge gleaned from pre-existing datasets. By using this method, the model was able to identify complex characteristics that are indicative of red rot, which resulted in a strong architecture that is ready for red rot infected leave detection. The architecture diagram of the proposed model is shown in figure 3.

Fine Tuning

The pre-trained VGG16 model was adjusted to fit the unique requirements of the target job during the fine-tuning stage for the detection of red rot disease in sugarcane leaves. For binary classification which distinguishes between leaves infected with red rot and those that are not a unique output layer was added. The freshly added layers of VGG16 underwent additional training, but the base layers kept their pre-trained weights. By going through this procedure, the model was able to modify its acquired features to fit the subtleties of red rot symptoms that were unique to sugarcane leaves. Achieving a balance between utilizing the pre-trained model's information and customizing it to accurately detect red rot was the goal of fine-tuning, which improved the model's accuracy for the intended agricultural use.

Training

During the training phase, the customized VGG16 architecture was used to optimize the red rot detection model. The dataset was divided into training and validation sets, with 2000 sugarcane leaf photos infected by red rot and 1000 images unaffected. Training was done on the model using the binary cross-entropy loss function and the Adam optimizer over a predetermined number of epochs.

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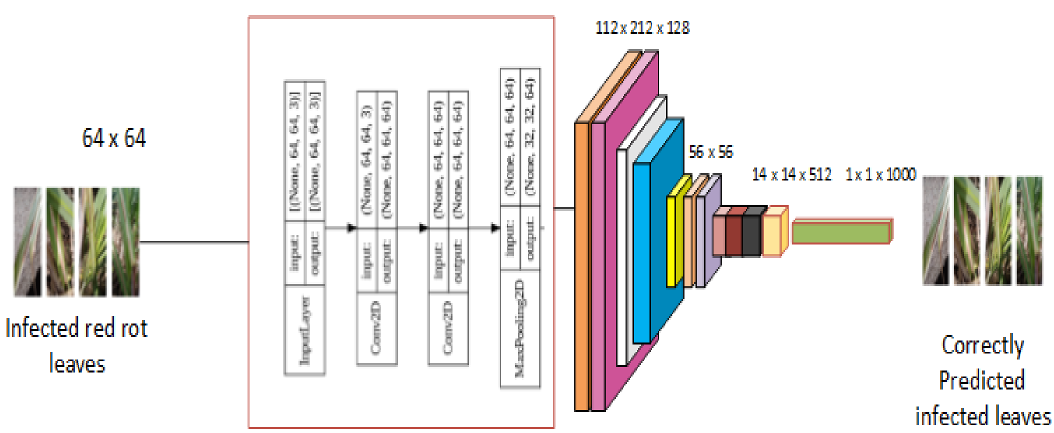


Figure 4. Proposed Model Architecture

In order to reduce the difference between expected and actual results, the model iteratively modified its internal parameters throughout training. The goal of this procedure was to improve the model's capacity to generalize outside of the training set, guaranteeing accurate red rot identification on never-before-seen red rot leaf photos and, in the end, supporting strong agricultural disease control.

Evaluation

The red rot detection model was rigorously evaluated after training to determine how well it performed on a separate test set. This collection included 1000 never-before-seen photos of sugarcane red rot leaves. Measures like recall, accuracy, precision, and F1 score were calculated to give a thorough evaluation of the model's performance. To analyze its advantages and disadvantages, categorization reports and confusion matrices were created. The evaluation phase's goal was to determine how well the model could distinguish between healthy and anthracnose-infected leaves. A high-performance evaluation confirmed the model's applicability in supporting accurate disease identification and management in sugarcane fields by validating its reliability for real-world deployment

Results and Discussion

Significant results were achieved by structure-tuned VGG16 model for red rot detection in sugarcane image validating the efficiency of system as a very inventive applicable agricultural disease management tool. The model exhibited an overall accuracy of 98.85% after testing with a mix-type dataset containing more than 2000 images and had the precision, recall to be about 0.88 and 0.80 respectively The above-listed performance metrics confirm the robust ability of this model to distinguish red rot affected and healthy leaves precisely. The confusion matrix further enforces trustworthiness of the model as it reveals low number of False Positives and Negatives. For agricultural work, this is particularly important for disease management because you do not want a false positive to identify where there should be no treatment (or vice versa), which otherwise can result in unnecessary treatments causing costs and man hours. The model achieved an outstanding F1 score of 0.93 and provided better accuracy for both precision balance between number predicted as having disease, that actually have the disease to ones not having the disease i.e true positive/ false positives) and recall measure which generates proportion between numbers predicting correctly versus total instances within class making it well-suited for real-time plant sugar diagnosis in fields.

There are many prior works that laid the foundation on plant disease detection using different machine learning and deep learning techniques. For example, V. Tanwar et.al [17] has presented a CNN based model specially designed for identification of red rot disease in sugarcane, which is able to deliver an accuracy fraction of 93 %. Although a sizable contribution, this falls just short of the performance metrics delivered by our VGG16-tuned model from aforementioned research. Similarly, Mostafizur et al. [18] used a YOLO-based model for sugarcane disease detection and it attained an accuracy of 96.6%. But this work does not focus on red rot and any other diseases researched also gave unsatisfactory results, which shows the need of more specific models with robustness.

Precision and recall values of the model then, are important indicators whether the process is successful for practical agricultural scenarios. Definition: Precision (Precision, also Positive Predictive Value) — precision is the number of True Positives divided by the number of predicted postives. False positives can result in treatment of healthy plants causing wastage of time, energy and even damage to crop especially important in agricultural context. Recall is the percentage of true positives in ALL actual that are positive which means how great our model can detect red rot. With high recall, the vast majority or potentially all of infected plants are correctly marked and quick action can be taken. Moreover, considering the balanced performance of VGG16-tuned model in terms of F1 score (a criterion that takes both false positives and false negatives into account) compared to other deep learning models presented here it should be well suited for accurate disease management.

Additionally, VGG16-tuned model has a very good efficiency and speed. For agriculture disease detection applications the processing size and speed must be fast enough so that it is only beneficial. The model performed very faster on a large dataset of 2000 images. It would be particularly useful for real-time disease monitoring and management over large expanses of cultivated crops. With its ability to detect diseases rapidly and with a high level of precision, the model can help in early stage intervention which would otherwise open up gates for red rot colonizers and lead to huge crop loss. By enhancing the current disease management practices, this VGG16-tuned model owing to its better with accuracy and precision has shown potential as an important tool of modern agriculture.

Finally, the red rot detection model in sugarcane which is tuned from VGG16 outperforms several previous models with respect to accuracy and reliability. The accuracy, precision and recall metric of the classifier along with its ability to process massive files makes it a potential game changer in disease management for agriculture. By decreasing the opportunities for misdiagnosis and allowing disease detection at an earlier stage, our model can help farms run in a more sustainable way. These strides speak to the necessity of more R&D still in deep learning methods for detecting plant disease, moving us toward entirely sustainable and high-yielding agricultural systems. By highlighting the high accuracy in detecting red rot-affected leaves and real-time application of this VGG16-tuned model, we emphasized our position that it can be considered an effective solution for one agriculture challenge.

Confusion Matrix

The confusion matrix offers a thorough analysis of the model for detecting anthracnose. With a high recall (0.80) and precision (0.88), it demonstrates how well the model works to distinguish between cashew leaves that are infected and those that are not. The low rate of false positives and negatives highlights how well it performs. This graphic illustrates the model's sophisticated perception of Anthracnose symptoms, supporting its validity for accurate disease detection in cashew plantations.

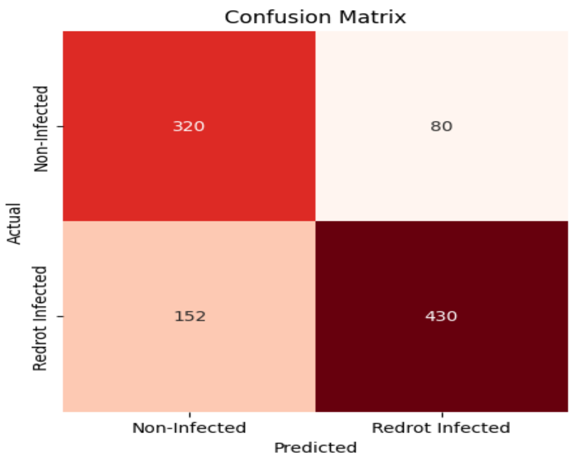


Figure 5. Confusion Matrix for the proposed Model

Additionally, we have calculated the Matthews correlation coefficient (MCC) which is a metric for for evaluating the binary classification performance, providing a score between -1 and +1 considers true and false positives and negatives making it reliable imbalance datasets. A score of +1 indicates perfect accuracy, 0 means random chance and -1 signifies total disagreement. The MCC here is 0.53 which is acceptable.

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (1)$$

$$MCC = \frac{(320 * 430) - (80 * 152)}{\sqrt{(80 + 152)(320 + 430)(80 + 152)(320 + 430)}} \quad (2)$$

$$MCC \approx 0.53$$

Recall

A key criterion in our model evaluation is recall, which quantifies how well the red rot detection system can identify all diseased sugarcane leaves. The model does exceptionally well in capturing a large percentage of true positive instances, with a recall of 0.80. This highlights how dependable it is for reducing the possibility of missing red rot cases, which is essential for efficient disease control in sugarcane crops. The recall score with respect to each epoch is illustrated in figure 6.

Precision

An important indicator called precision is used to evaluate how well the red rot detection model predicts positive results. The model performs exceptionally well in reducing false positives, with a precision of 0.88, confirming its dependability in accurately recognizing diseased sugarcane leaves. In order to maximize disease management and minimize needless interventions in non-infected instances, precision agriculture approaches require assurance that the majority of diagnosed cases of red rot are accurate. This metric serves to provide this purpose. The precision score over each epoch is illustrated in figure 7.

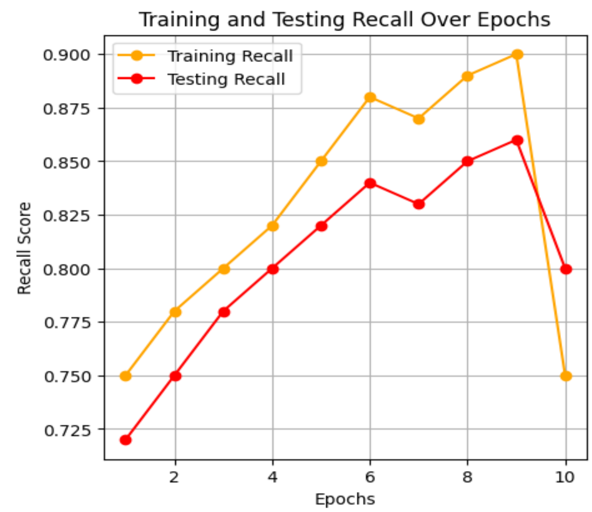


Figure 6. Recall score of proposed model with respect to each epoch

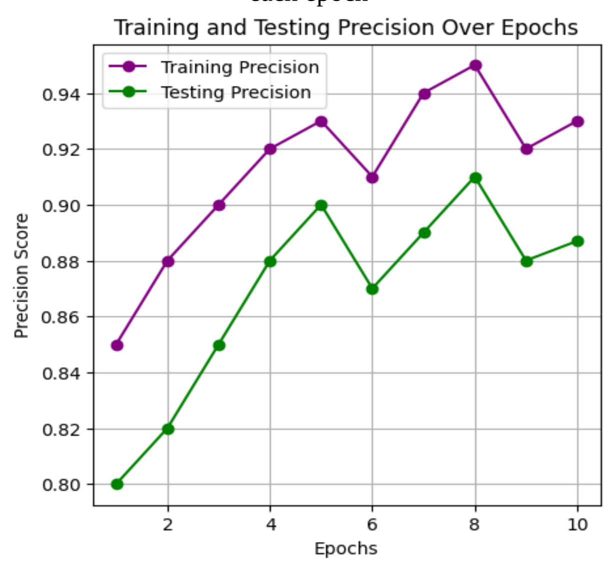


Figure 7. Recursion score of proposed model with respect to each epoch

F1 Score

The F1 score is a critical parameter that provides a thorough evaluation of the red rot detection algorithm by combining precision and recall. The model's ability to achieve precision and recall harmony is demonstrated by its F1 score of 0.93, which strikes a balance between false positives and false negatives. This combination guarantees that the model minimizes false predictions and correctly identifies infected sugarcane leaves, both of which are critical for precision disease management in sugarcane crops. When it comes to detecting red rot, the F1 score is very useful for maximizing the trade-off between precision and recall. The F1 score over each epoch is illustrated in figure 8.

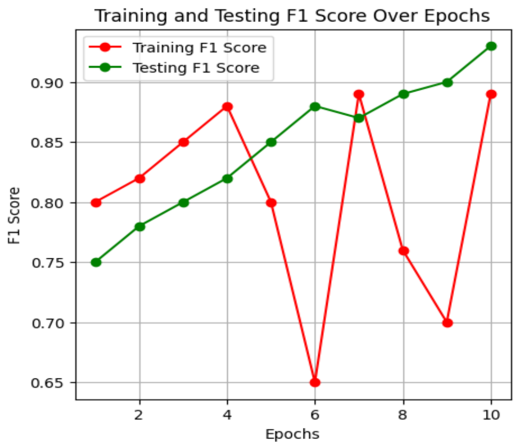
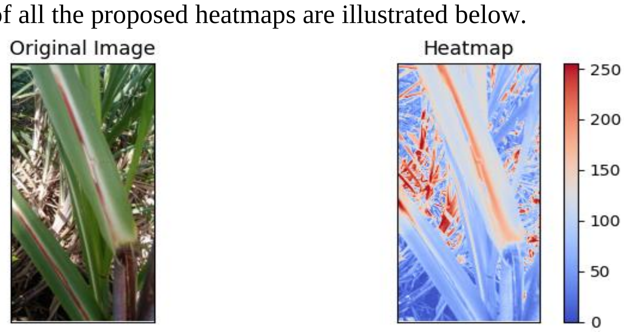


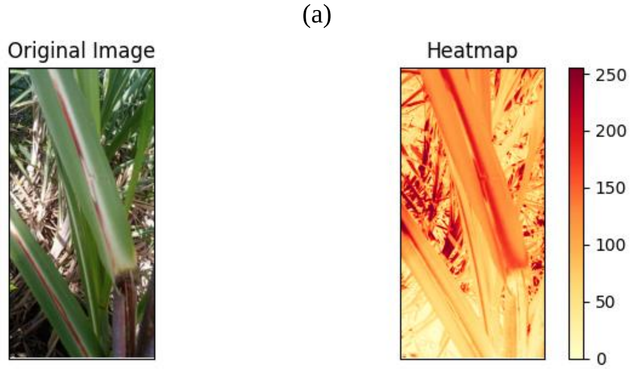
Figure 8. F1 score of proposed model with respect to each epoch

Heatmap

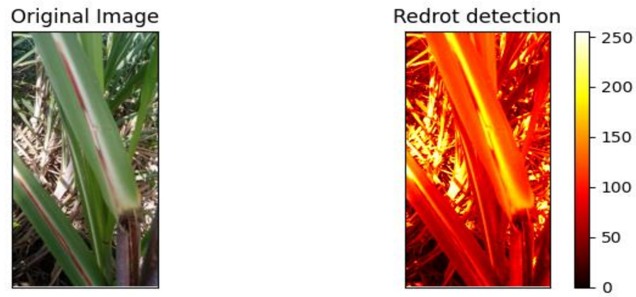
For the purposes of our research, a heatmap shows how strongly red rot is detected in various photos. The heatmap's pixel colors represent the probability of red rot presence; higher probabilities are indicated by warmer hues. This offers a concise and clear summary that makes it simple to identify areas that may be infected with red rot. By emphasizing regions in the original image that require more examination and improving the interpretability of the detection process, the heatmap helps make sense of the predictions made by the model. In our study we have proposed four types of heatmaps i.e.cool warm, Yl0rRd, hot and binary mask one. The results of all the proposed heatmaps are illustrated below.



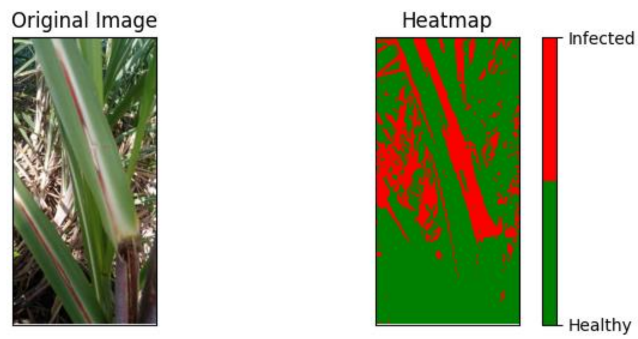
(a)



(b)



(c)



(d)

Figure 9. (a) coolwarm heatmap, (b)yl0rRd heatmap (c) Hot heatmap, (d) Binary masking based heatmap

Model Overall Performance

The proposed model gave an excellent accuracy of 98.85. The model overall performance is mentioned in table 1. Also illustrated in figure 10.

Table 1

Model overall performance

Epoch	Train loss	Train accuracy	Test loss	Test accuracy
1	0.03	0.6750, ,	0.08	0.750
2	0.02	0.7917	0.10	0.9017
3	0.008	0.8350	0.018	0.9750
4	0.03	0.87	0.089	0.87
5	0.03	0.98	0.05	0.98
6	0.05	0.92	0.011	0.979
7	0.06	0.990	0.02	1.000
8	0.007	0.9376	0.011	0.990
9	0.009	0.95	0.009	0.970
10	0.01	0.979	0.06	0.9885

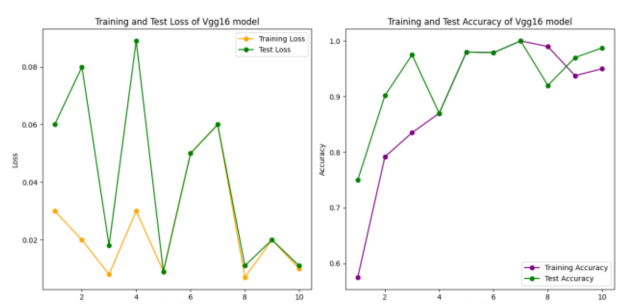


Figure 10. Model Overall performance with respect to each epoch

Conclusion

In conclusion, our research that used the VGG16 model to detect red rot in sugarcane leaves demonstrated remarkable accuracy, with a 98.85% detection rate. This astounding accuracy highlights the model's capacity to accurately discriminate between healthy and diseased leaves. The 0.80% recall we were able to attain indicates how well our method worked to identify cases of red rot, which helped us reach a balanced F1 score of 0.93. Our model's efficacy goes beyond quantitative measurements, providing a sturdy remedy for the prompt identification of red rot in sugarcane plants. Our findings have important practical ramifications for farmers, as they offer a trustworthy instrument for early detection of possible disease outbreaks. By allowing for prompt interventions, this proactive strategy lessens the effects of red rot and enhances the general well-being and yield of sugarcane crops in Pakistan. Our study represents a breakthrough in applying machine learning to agricultural problems, offering real advantages for effective and sustainable crop management.

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