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Deep Learning Based Detection of Corn Stalk Diseases with XAI

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Abstract:- This research aims at developing a deep learning model for corn stalk disease detection (for anthracnose disease) using explainable AI approaches, Grad-CAM. Based on the CNN deep learning models, the proposed system is developed. For inputs including images of corn stalks, the system prepares them, generates visual descriptions of the layer, and correctly categorizes the image as being related to a healthy corn plant or a diseased one. Overall, it plays a part in enhancing explainability of model predictions to the end user, especially the uninitiated in the aspect of some level of understanding. However, the system significantly saves training time and computational expense by using transfer learning without a decline in accuracy.

Keywords:- *Deep Learning, Grad-CAM, Convolutional Neural Networks, Image Classification, Explainable AI.*

I. INTRODUCTION

Corn is among the most productive and dominant crops grown around the world today. However, corn production faces significant challenges due to various diseases, including those affecting the stalk [1]. Stalk is the main part of the corn plant, and it should be very strong in terms of handle the weight of the corn ears and creating paths for the nutrients to run in them [2]. Anthracnose disease is a common fungal disease that softens the stalks, reduces yield and, in severe cases, results in the failure of the crop [3].One of the important factors in the disease control and reduction of their effects is its initial and proper diagnosis.

➢ *Anthracnose Disease in Corn Stalks*

Currently there is limited research specifically targeting corn stalks diseases, especially anthracnose disease. These diseases have unique patterns, existing systems fail to identify. Therefore, disease detection in corn stalks relies on manual inspection. But it is time consuming, subjective and can be prone to errors more often.

➢ *Motivation*

Most existing research in the domain of corn disease detection has primarily focused on corn leaves rather than the stalk. Out of the very few research, there is no evidence for anthracnose detection. This disease is causing significant yield losses, impacting food security and economic well-being, particularly for smallholder farmers. To address this challenge, this research proposes an AI-driven corn stalk disease detection system that leverages deep learning for accurate predictions and Grad-CAM for explainability.

II. LITERATURE REVIEW

➢ *Corn Stalk Disease Detection*

Corn stalk diseases have unique patterns, therefore, most of the existing disease detection systems find it difficult to identify them with higher accuracy. Therefore, disease detection in corn stalks relies on manual inspection, which is time consuming, subjective and has more chance for errors. Also, another key issue is that these diseases are identified when the symptoms are very visible, which means late detection [4]. By that time, it'll be too late for diagnosis. Also, another challenge in making a system to identify corn stalk diseases is lack of properly labelled, high quality, publicly available dataset. This is one of the main reasons for not having much research on corn stalk diseases.

➢ *Image Processing and Deep Learning in Agricultural Disease Detection*

Edge detection, contrast enhancement, noise reduction processors are some pre-processing techniques used in image processing. [5].These methods also focus on the subject selection, what type of features of corn stalks indicate disease, like lesions or discoloration. Disease symptoms are generally identified using deep learning models, mainly CNN after some level of processing. CNNs can be trained directly on raw image data to provide raw hierarchical features that are ideal for disease detection of complex patterns in plant disease.[6]

Deep learning models such as AlexNet, VGGNet, RESNet, have been used for plant disease detection, obtaining high accuracy for plant types [4]. Given big datasets of labeled images from which these models can be trained, it can be taught to distinguish between healthy plants and diseased plants based on feature, if trained on.

Transfer learning refers to the practice of utilizing a pre-existing model that has been trained on a different but similar problem. The corn stalk disease dataset is employed to further train algorithms the foundational architecture of which was created on vast image datasets. This strategy builds from existing information to not require a large amount of data and resources to train effective models from scratch.[7]

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Image augmentation is a method used to enhance the variety of the training dataset without the need to gather more data [5]. To increase reliability of machine learning models and prevent model overfitting on maize stalks, image preprocessing is applied as rotation, scaling or flipping of the image. Normalization, contrast adjustment and noise reduction are among the data pre-processing methods performed on the images in order to improve the efficiency of machines learning algorithms. On one hand, preprocessing ensures that the input photos are in a uniform format, and eases recovery of better features by the models.[6]

➢ *Explainable AI in Agriculture*

Deep learning models reach high accuracy, but their 'black box' nature prevents user from understanding how the decision is being made. In agriculture especially farmers and agricultural experts want to trust the predictions made by these models and this becomes a problem. Explanation of AI (XAI) explains this problem by giving insights into the model's decision-making process. To produce visual explanations for predictions of the models XAI techniques such as Grad-CAM, LIME, SHAP can be used as it highlights the part of an image that most affected the model's prediction. [8]

Gradient based methods like Grad-CAM produce heatmaps on input images and highlight the areas that influenced model's predictions in identifying plant diseases [9]. LIME explains individual predictions by approximating intricate models with comprehensible ones, offering insights into the features (e.g., leaf colour, texture) that influenced the disease detection decision. SHAP measures the impact of each variable on the model's output, facilitating the identification of specific characteristics (e.g., size, spots, or colour of lesions) influenced illness classification.

Explainable Artificial Intelligence (XAI) methodologies are progressively utilised in agricultural disease identification to enhance the transparency, interpretability, and reliability of AI-driven judgements for farmers and researchers. Through incorporating the XAI into the disease detection system, the model is not a black box as it assists disease identification while explaining its decision-making process. In particular, the field where the deployment of such systems can have critical implications, accurate predictions are crucial.

III. EXISTING WORK

Several works have already shown the capability of deep learning in detecting plant diseases. [10] for instance used a deep convolutional neural network (CNN) to categorize 38 different plant diseases at an accuracy over 99%. Similar to predicting diseases on corn stalks where signs that are evident include lesions, discolorations, or fungal growths on the stalks and leaves, the study centred its research on the ability of image pattern recognition of the CNN to predict the patterns in the images of the leaves.

Similarly [4] applied deep learning models such as AlexNet and VGGNet to plant disease detection, obtaining high accuracy for plant types. Large datasets of labeled images from which these models can be trained, can teach it to differentiate healthy plants from diseased plants based on feature, if trained on.

Sometimes deep learning models achieve very high accuracy, but this approach puzzles the user because the detailed rationale of how the decision was made cannot be explained. In agriculture especially farmers and agricultural experts want to trust the predictions made by these models and this becomes a problem.. [9] research has shown that Grad-CAM can provide meaningful explanations for deep learning models in different domains such as plant disease detection.

IV. PROPOSED APPROACH

The author proposed to develop a deep learning-based system for detecting corn stalk diseases, with a focus on anthracnose, by utilizing ResNet50 for disease prediction and incorporating Grad-CAM for explainability, ensuring high accuracy and interpretability for real-world agricultural applications.

➢ *Dataset*

The author made a dataset by combining two publicly available datasets in Kaggle and labelled it with the help of domain experts. The made dataset consisted of 600 images as 300 images of stalks with anthracnose disease and 300 images of healthy stalks.

Fig 1 Samples of the Dataset

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➢ *Data Pre-Processing*

The author has split the dataset into three sets as 70% of the total dataset used for training, 15% used for validation and the remaining 15% used for testing. Additionally, the author has mentioned that data augmentation techniques were used during the training process to increase diversity of the training set and improve model's ability to generalize to new, unseen data.

➢ *Training the Model*

The author trained the model for 30 epochs on a dataset and evaluated the performance using training accuracy/loss and validation accuracy/loss. The model achieved high accuracy on both training and validation data which indicates that it learned to make accurate decisions. At the same time the loss values also decreased gradually which shows the confidence in model's predictions. The also tried different hyperparameters to reduce overfitting.

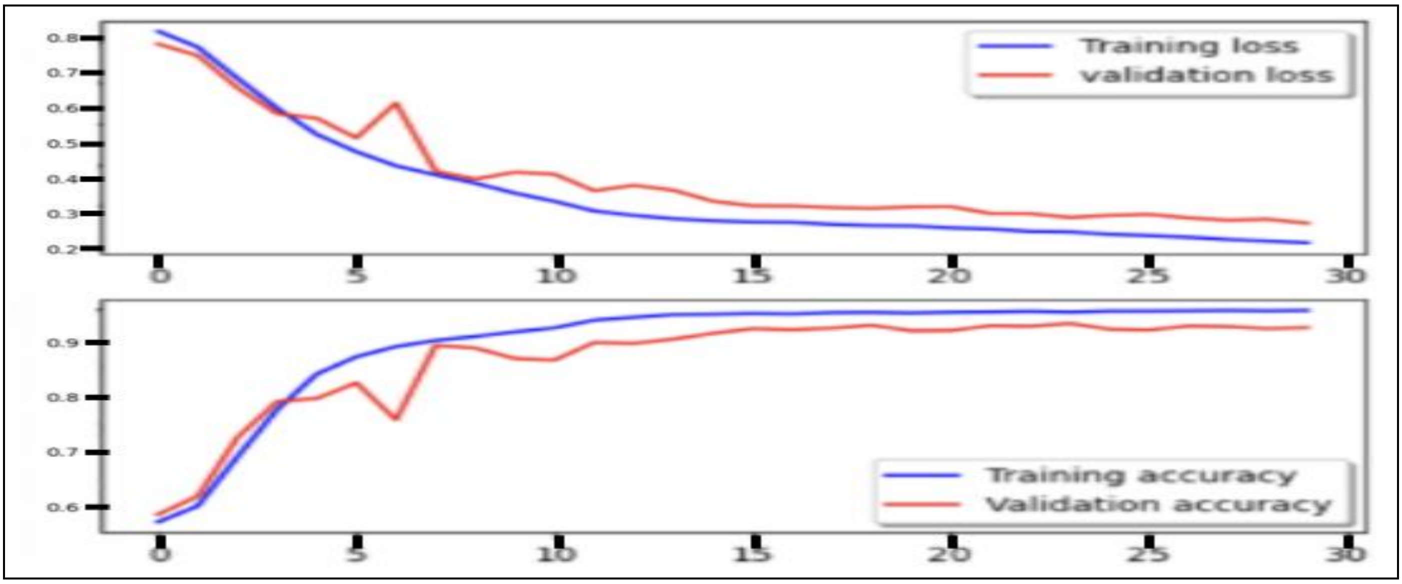

Fig 2 Training and Validation Loss

➢ *Hyper Parameter Tuning*

The author has used EarlyStopping which monitors the validation loss and stops if there is no improvement for 5 consecutive epochs. Also, the author usedReduceLROnPlateau and the minimum learning rate is set to 0.00001. These hyperparameter tunings helped to prevent overfitting and ensure model is generalized well to new data.

V. EVALUATION

➢ *Classification Report*

For the evaluation of the model's performance, the classification report for test data is used. It shows metrics like precision, recall and F1-Score. The model achieved an accuracy of 94% and a recall of 0.91. The precision of the model is 0.98. The F1-Score which is a harmonic mean of precision and recall is 0.95, indicating that the model has a good balance between precision and recall.

```
[124] from sklearn.metrics import classification_report

y_true = test_generator.classes
y_pred = model.predict(test_generator)
y_pred = np.where(y_pred > 0.5, 1, 0)

print(classification_report(y_true, y_pred, target_names=['Healthy', 'Diseased']))

3/3 ━━━━━━━━━━━━━━━━━━━━ 4s 1s/step
              precision    recall  f1-score   support

     Healthy       0.92      0.98      0.95        45
    Diseased       0.98      0.91      0.94        45

    accuracy                           0.94        90
   macro avg       0.95      0.94      0.94        90
weighted avg       0.95      0.94      0.94        90
```

Fig 3 Classification Report

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➢ *Confusion Matrix*

Confusion Matrix is used for the evaluation of the model. The low number of misclassifications reflected in high accuracy. 90 images were used for testing (45 healthy and 45 diseased). Out of the 45 anthracnose diseased stalks, 41 were predicted correctly and only 4 were misclassified. Out of the 45 healthy stalks only 1 was misclassified.

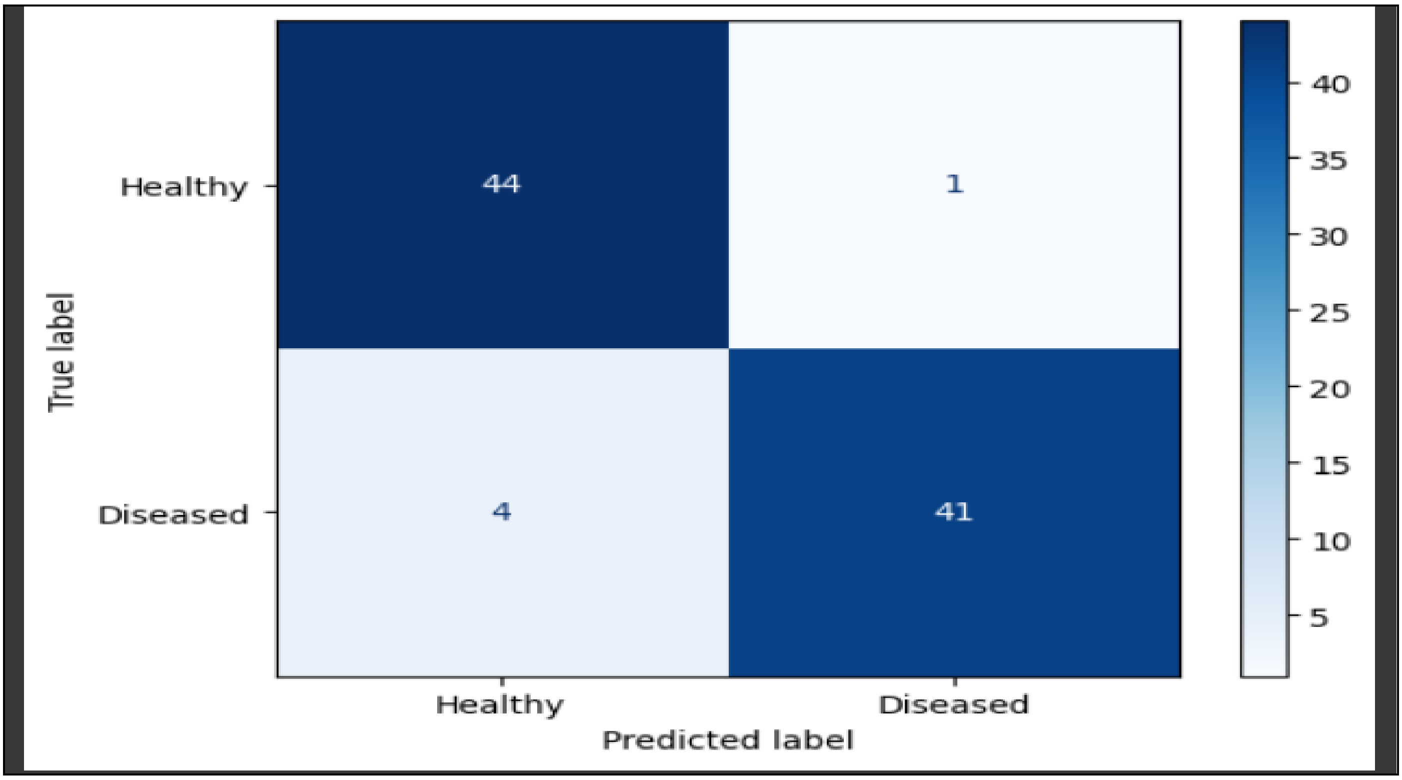
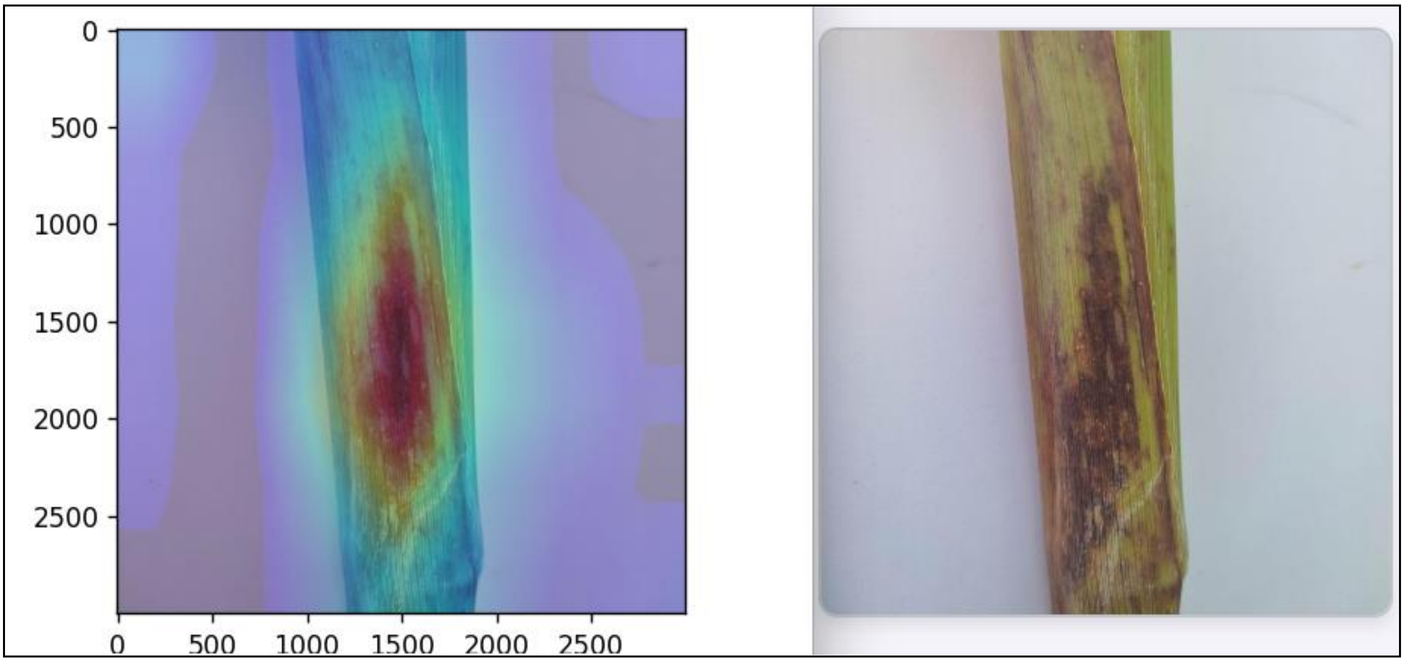


Fig 4 Confusion Matrix

➢ *Grad-CAM Heatmaps*

The author has used Grad-CAM (Gradient weighted Class Activation Mapping) to explain the predictions made by the model. Grad-CAM is an XAI (Explainable Artificial Intelligence) technique which helps for understanding of model's decision-making process by highlighting the important features which was used by the model for the predictions. The generated Grad-CAM heatmaps have shown that the model is accurately identifying the symptoms for anthracnose disease in corn stalks. By comparing with the original image most of the regions that contains symptoms are highlighted in the heatmaps.



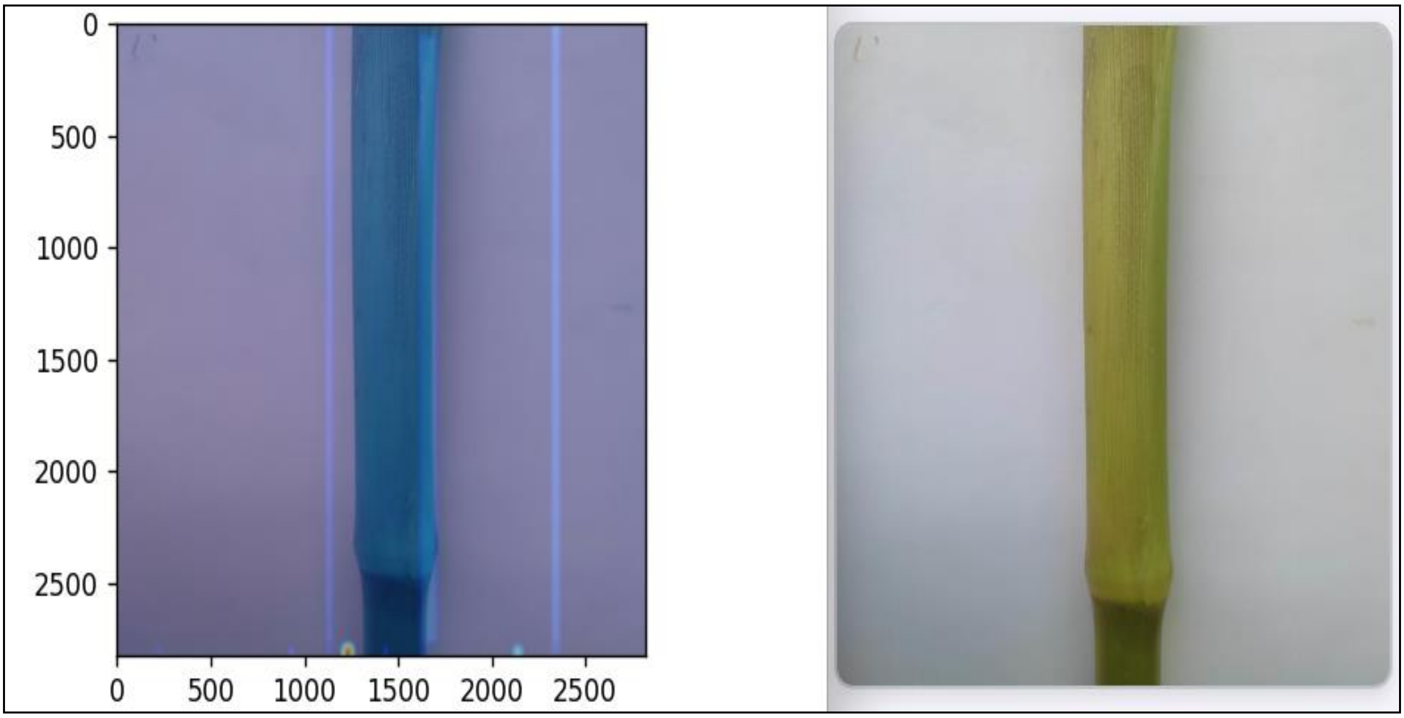


Fig 5 Heatmaps vs Original Image

VI. DISCUSSION

The research done by the author highlights the challenging task of identifying corn stalk diseases, especially anthracnose disease. This is a significant issue in the domain of agricultural disease identification, where most of the systems either focuses on leaves or the whole plant. The research is an important contribution to this field as it addresses a critical challenge and proposes a solution for it.

In addition, for the proposing of the corn stalk disease identification system, the author also has incorporated XAI techniques like Grad-CAM to improve interpretability. This is particularly important as explainability is a key factor in ensuring the reliability and trustworthiness of the system.

VII. FUTURE ENHANCEMENTS

As for the future enhancements, the author will develop a mobile application to allow farmers in remote areas to quickly upload images of corn stalks and receive predictions in real time. Also, the author will explore more XAI techniques like a hybrid approach to improve the interpretability more.

VIII. CONCLUSION

In conclusion, this research successfully developed a deep learning-based corn stalk disease detection system using ResNet50 and Grad-CAM for interpretability, achieving high accuracy on unseen data and providing valuable visual explanations for model decisions. Through rigorous evaluation and testing, the system has demonstrated its ability to address a real-world agricultural challenge, contributing to both research and practical use.

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