STRAWBERRY PLANT DISEASE DETECTION USING U-NET SEGMENTATION AND XGBOOST CLASSIFICATION

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Abstract **Despite being one of the horticultural crops with the highest economic value, strawberries are extremely vulnerable to bacterial and fungal infections. To reduce yield losses and guarantee sustainable cultivation, early and precise disease detection is crucial. This is also the first research where an integrated technique that uses machine learning and deep learning to classify diseases of strawberry plants is developed. A U-Net segmentation model is first used to determine the locations of diseased strawberry plants, based on the images of their leaves which the model has been trained on. During training, K-fold cross-validation is utilized to ensure the model is optimally trained such that it can generalize on new samples. After some extra steps, special features that help in distinguishing between different classes are taken from the segmented results to perform the classification.An XGBoost classifier is then used to categorize the leaves into classes that are either healthy or diseased. K-Means clustering is used as a preprocessing step for better lesion feature extraction. Based on experimental results, the suggested framework provides 92% classification accuracy and roughly 90% segmentation accuracy (Dice coefficient). Due to its effectiveness and dependability in computerized disease detection in strawberry plantations, this combination approach holds great potential for application in precision agriculture.**

Keywords Deep Learning, Machine Learning, Computer Vision, XGBoost, K-Means Clustering, Image Segmentation, Strawberry Leaf Disease, Convolutional Neural Network (CNN), U-Net, Precision Agriculture.

1.INTRODUCTION

Plant diseases can negatively impact agricultural production by significantly lowering crop yields and quality. Even though strawberries rank among the global most cultivated horticultural crops, during growth they are particularly susceptible to bacterial and fungal infections, including leaf spot, leaf scorch, and grey mold. In order to avoid grave losses of yield, it is crucial to recognize the signs of these infections. Manual methods for plant disease diagnosis rely heavily on the judgment of specialists, and often lead to considerable delays and errors, along with unnecessarily high expenses. These shortcomings, alongside the development of computer vision and AI, are what drove automating plant disease diagnosis. It is now possible to recognize and identity various types of plants with images, thanks to the intricate work of convolutional neural networks (CNNs) in pinpointing and classifying plant diseases.Nevertheless, a lot of current methods mainly concentrate on image-level classification, which is limited to determining if a plant is healthy or sick. These methods are less useful in real-world agricultural situations where farmers need to know the extent and spread of infection because they are unable to pinpoint the exact location of lesions. Pixel-level image segmentation methods have therefore gained popularity since they offer precise localization of diseased regions.

This study advances the use of machine learning for classification and deep learning for image segmentation by proposing new methods for identifying diseases of strawberry leaves. The primary segmentation unit uses U-Net as the base architecture which is widely adopted for biomedical and agricultural imaging due to the architecture's encoder–decoder design and skip connections. The U-Net model is trained using strawberry leaf images and the corresponding ground-truth segmentation masks. To minimize model overfitting and establish the model's ability to generalize to new data, k-fold cross-validation is employed in the course of training.The dataset is extended with a data generator to include variations in lighting, orientation, scale, and other minor changes. The additional training dataset includes numerous augmentations such as flipping, zooming, translating, and rotation..

After classifying the diseased areas and creating and forwarding the discriminative features to it, an XGBoost classifies the remaining diseases as healthy or diseased. XGBoost was selected due to its ability to provide more accuracy with structured features of data, its scalability, and overall great performance. To more limitedly delineate lesions, a preprocessing method of K-Means clustering was chosen to help establish groupings of pixels into similar clusters to better differentiate between healthy and diseased area.

With leaves being classified as healthy or infected and the actual infected areas being identified, this approach would provide essential information for farm decision making through higher precision. Experimental testing shows that the U-Net segmentation model classifies hoping lesion areas with good accuracy, while the XG classifier increases the accuracy of the overall classification. This two-part method can be helpful for agricultural management through a reliable local disease detector and a full auxiliary check of leaf health.

II.LITERATURE SURVEY

The literature regarding identifying plant diseases through computer vision and deep learning has been developing. Deep learning, as noted by Mohanty et al. [1], was applied for the first time to classify the different species of crops as well as accurately classify the diseases afflicting them at an unparalleled scale, through the use of the Plant Village dataset which acts as a classifier trained library. With the help of this research, it was possible to demonstrate the capability of deep learning for the purposes of disease diagnosis in the agricultural field.Based on this, Ferentinos [2] used CNN architectures to find plant diseases in real time, which is possible for many crops including tomato and grape.

The work by Ronneberger et al. [3] on the U-Net model for improved lesion locatization first introduced for the biomedical image segmentation task and is now widely used for agricultural image processing purposes. It was Polder et al. [4] who first demonstrated the applicability of the architecture for non biomedical data by employing U-Net for segmentation of diseased tulips. Likewise, Brahimi et al. [5] used CNNs for agriculture plant disease recognition where the concept of transfer learning is applied for pretrained networks case agri datasets are insufficient.

Also causing ripples are hybrid approaches that integrate machine learning and deep learning. Too et al. [6] identified that gradient boosting models like XGBoost are extremely accurate when there are well-engineered features. They were evaluated alongside competitively trained CNN s and classic ML s such as Random Forest, Support Vector Machines, and XGBoost. Proposed by Chen and Guestrin, XGBoost [7] uses scalable and interpretable features, which is why it has been used for plant phenotype characterization and disease classification since its inception.

Prior to leaf disease classification, researchers have explored methods of feature extraction and preparation without requiring labeled data. For better discrimination between healthy portions and disease portions, Singh and others [8] utilized a procedure known as K-Means clustering to divide leaf images on the basis of color. Likewise, Al-Hiary and his group [9] utilized clustering procedures to distinguish between citrus leaf diseases, and the study illustrated that pre-preparation of data helped it to raise the accuracy of disease classification.

For detection studies in plant diseases, K-fold crossvalidation has been extensively recommended as a strategy to reduce overfitting and increase robustness. Crossvalidation is important to properly evaluate the model, particularly with small agricultural data sets, Sladojevic et al. [10] believed. According to recent reviews on deep learning plant pathology summarized by Barbedo et al. [11] and Saleem et al. [12], the most capable classifiers are XGBoost, and for segmentations, U-Net.

Zhang et al. [13] explains the application of CNN augmented model on data sets on classification of strawberry leaf diseases and how useful data augmentation performed in enhancing accuracy. Wang et al. [14] used transfer learning along with popular model frameworks like ResNet and InceptionV3 for improving the performance of small strawberry datasets. Li et al. [15] advanced this further by merging classification with U-Net segmentation so that diseases can be classified, in addition to identifying the more targeted areas of strawberries that are infected. These methods serve as the foundation for our proposed hybrid technique that incorporates XGBoost classification, KMeans clustering, and U-Net segmentation for detecting diseased strawberry leaves.

III.METHODOLOGY

The approach that has been suggested for strawberry leaf disease recognition is a hybrid model of machine learning, unsupervised clustering, and deep learning. The following steps represent the entire workflow, as shown in Fig. 1:

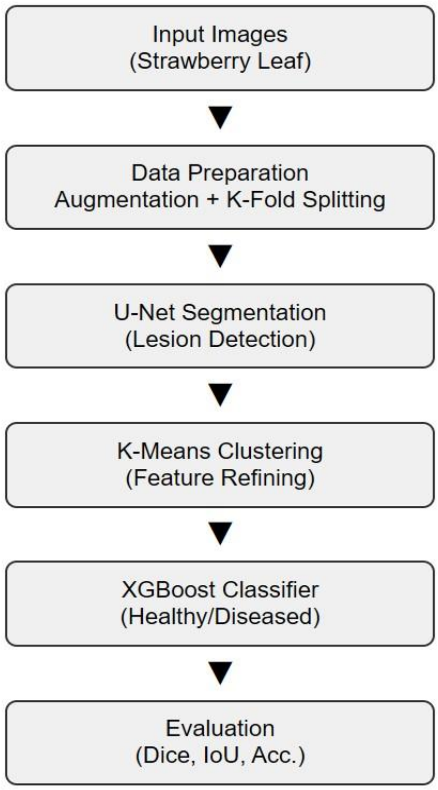

Fig.3.1. Flow Diagram of Proposed Methodology

A.Preparing Data

The dataset has pictures of strawberry leaves along with masks indicating weak points of the leaves. A plethora of image altering techniques were used to ensure the model effectiveness in multiple scenarios. These were flipping, rotating, zooming, and shifting the pictures. With these transformations, the model could adapt to different sizes, light, and rotation. To provide a baseline to the model, the dataset was added using a k fold cross-validation. This method splits the dataset into k number of subsets. From the k subsets, once k-1 are trained, the k-th set is used to test the model. This continues so that all subsets are used once as the test set. The final evaluation is done using the average of the individual evaluations. This method prevents the model from overfitting ensures the model can adapt to new unseen data.

B. Segmentation using U-Net

The U-Net architecture due to its efficiency in biomedical and agricultural imaging, was assigned for the principal segmentation task. The U-Net model employs encoder-decoder architecture where the encoder analyzes the image and the subsequent decoder employs the encoder's key feature representations to render a detailed spatial mask. To be able to detect small lesions, very detailed and irregular in shape, fine details have to be preserved, hence the use of skip connections in the encoder-decoder pairs.

The U-Net model was trained using images of size 512 x 512 x 3. In the training process, there was an attempt to achieve a good trade-off between the accuracy of predicting each pixel individually, and the overall fidelity of the predicted masks to the actual images. The model was trained using a combination of binary cross-entropy and dice loss. The model was trained for 50 epochs and the sbest version was stored in .hdf5 format which was to be used for the test data.

C. Preprocessing with K-Means Clustering

K-Means clustering was used as a preprocessing step on segmented outputs to further improve lesion visibility. An unsupervised algorithm called K-Means clusters image pixels according to how similar their colors and intensities are. By emphasizing areas with noticeable discoloration, clustering aids in the separation of healthy tissue from diseased areas in strawberry leaf images. In cases of mild infection where boundaries are difficult to discern, this step improves lesion features.

D. Classification using XGBoost

There and then, despite the dissection yielding accurate masks of the diseased areas, there is a need for classification at the image level. Hence, the XGBoost algorithm. XGBoost is a type of ensemble method which sequentially builds decision trees for which it optimizes the error of each of the trees. It is particularly well known for its ability to deal with unbalanced datasets, its speed, and its ability to scale. The XGBoost classifier in this case was trained on the features derived from the segmented images. The classifier then proceeded to assign the leaves into two classes: diseased and healthy. The reason this two-step process, where one can first observe the classification and then the segmentation, works so well in this scenario is because the classification in this case is specifically focused on the lesions, and not the entire image.

E. Evaluation Metrics

The performance of the proposed framework was evaluated using standard techniques. To evaluate the segmentation of the predicted masks against the ground truth annotations, the Dice Coefficient and Intersection Over Union (IoU) methods were used. The Dice score increases as the localization of lesions improves, and IoU quantifies the overlap between predicted and ground truth disease-affected regions. The classification was measured using F1, recall, accuracy, and precision. F1 score is the balance between precision and recall. Precision is defined as the diseased leaves the model predicted as diseased, while recall is defined as the diseased leaves the model actually predicted as diseased. These two measures provide a true idea of how well the framework performs.

IV.RESULTS

The suggested hybrid system's ability to recognize and detect diseases of strawberry leaves was verified. Testing was done on different folds using k-fold cross-validation to provide resistance and fairness in performance measurement. The segmentation, classification, and visualization experiment results are presented in detail below.

A. Segmentation Results

A major goal of this research was to perform disease segmentation on strawberry leaves at the pixel level. Analysis of the input image, predicted mask, and ground truth annotations is indicative. The U-Net model successfully captured lesions of varying sizes, shapes, and intensities. For the case of small and sparse damaged sites, the model was highly sensitive and missed few false positives. Likewise, when lesions became more abundant on the leaves, the segmentation masks were able to confidently outline the lesions' boundaries. The similarity between predicted masks and ground truth annotations is a testament to the model's exceptional ability to generalize to novel test samples.

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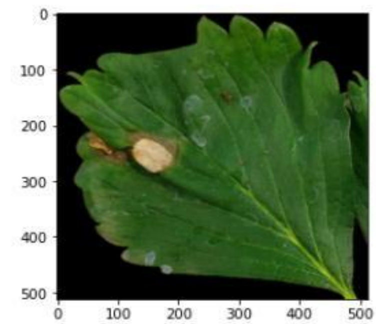

Fig.4.1. Input Images

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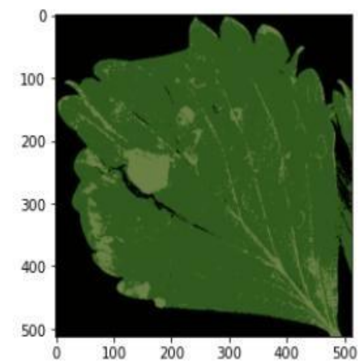


Fig.4.2. Predicted Masks

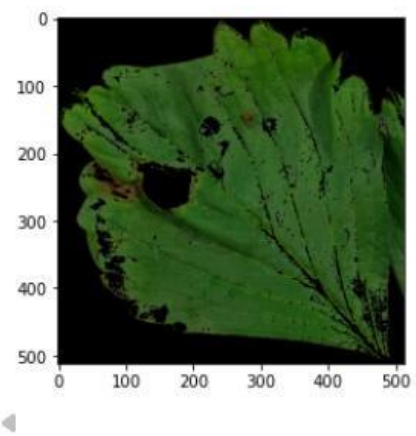


Fig.4.3. Ground-Truth masks

B. Training Performance

In Fig. 3, the performance of the U-Net model which trained and validated more than 50 times is illustrated. The graph indicates the accuracy and loss of both parameters.The model didn't overfit too much, as the line of accuracy remained constant and the validation accuracy was closest to the training accuracy possible. Loss also decreased steadily, indicating that the model trained well.

From the result point of view, the end segmentation was 0.88 for Intersection over Union (IoU) and approximately 0.90 for Dice coefficient.These are very good numbers as it indicates our predicted masks are nearly identical to the ground truth. The results indicate the approach performs well even with varying leaf texture and background and can accurately position diseased regions with confidence at the pixel level.

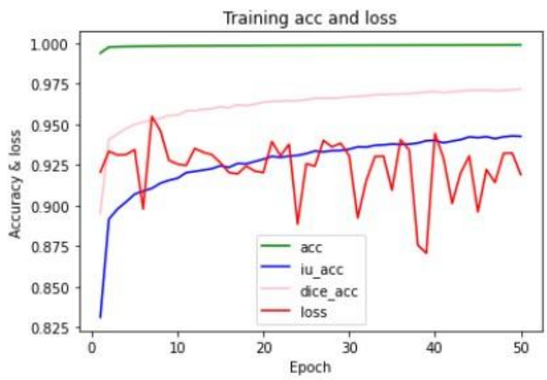


Fig.4.4. Illustrates the training accuracy and loss curves for the U-Net segmentation model.

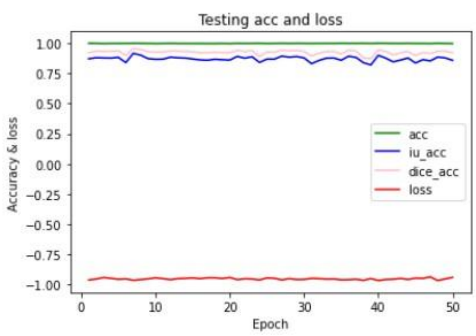


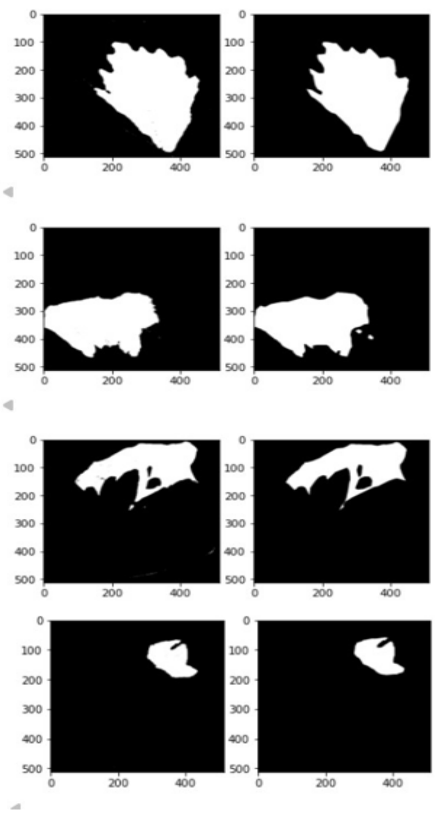
Fig.4.5. Presents the testing accuracy and loss curves for the UNet segmentation model.

C. Classification Results

With the data now split, the XGBoost classifier was employed to classify the samples into the 'sick' and 'healthy' classes relative to the features from the given areas.The model had high accuracy and recall of the sick and healthy classes, leading to an overall average test accuracy of approximately 92%. Most of the samples belonging to both the classes were correctly identified by the confusion matrix. There were effectively no misclassifications and these in general occurred in borderline cases with small or visually ambiguous lesions. Efficiency of classification was increased, and noise was decreased, when dense lesion features from segmentation rather than learning from full images were utilized. Experiments like these show the utility of combining deep learning segmentation and gradient boosting classification. Though the CNN-based classifiers can be fine-tuned to give high accuracy, they are explainability-lacking in their predictions. The hybrid model is, however, more appropriate for agricultural practical application due to the fact that it makes strong class predictions and readable lesion maps as well.

D. Visualization of Feature Maps

By analyzing specific portions of the U-Net feature maps, the intricate workings of the model became more well-defined.Figure 4 shows examples of how feature maps from early, middle, and deeper layers highlight different parts of the input image. The early layers mostly picked up on simple details like edges, colors, and leaf textures. These features help tell the leaf apart from the background. In the middle layers, the model started to recognize more complex things, like the shape of the leaf and the edges of any spots or damage. Finally, the deepest layers removed extra background details and focused only on the areas of the leaf that are unhealthy.



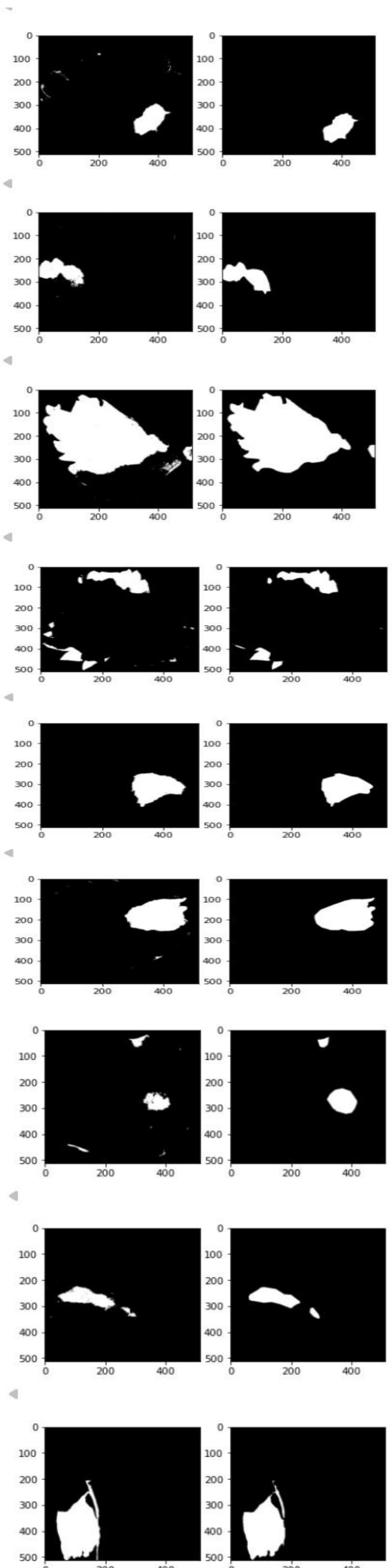


Fig.4.6. Feature map visualizations from different layers of U-Net.

V.DISCUSSIONS

Using K-Means preprocessing, U-Net segmentation and XGBoost classification, this strawberry disease detection system achieved better results in localizing lesions and diseases. The segments had reasonably high precision for scoring with a Dice score of roughly 0.90 and an IoU was roughly 0.88, which was indicative of true boundary detection of lesions including small, odd, or abnormal lesions. The final model showed underwent methodical training as the training and validation curves converged with slight overfitting to achieve best practice. The classification method also benefited from improved precision and recall which netted us roughly 92%. The errors of misclassification were a rare occurrence, and occurred more frequently when the features that were being classified were not strong and not displaying a pattern that was distinct from each other. The hierarchical learning capacity of the U-Net was further substantiated using visualizations of feature maps, in combination with training the model, where the deepest layers were attending to all the differentiations of the lesions, the shallow layers were focusing on texture, and other middle layers were citing evidence of edges. The method is easier to ultimately understand and significantly more relevant to precision farming context than all current state-of-the-art CNN based systems, because it was able to determine if disease state was present, or simply identifying the spatial location of where the infested locations were located.

VI.CONCLUSION

This study created a combined system that uses machine learning for classification and deep learning for segmentation to identify strawberry leaf disease. K-Means clustering improved lesion representation, while the U-Net architecture effectively and accurately segmented diseased areas. With a 92% classification accuracy, the XGBoost classifier proved how well lesion-specific features and gradient boosting work together to make decisions. This work's main contributions are as follows: an approach to segmentation at the pixel level that yields lesion maps that can be understood. incorporating unsupervised clustering to improve the visibility of lesions. XGBoost is used in this hybrid classification stage to provide reliable disease classification. This framework can be expanded in subsequent research by using bigger and more varied datasets for training, adding sophisticated models like Vision Transformers (ViTs) for segmentation, and implementing mobile device-optimized lightweight models to facilitate real-time field applications. Furthermore, adding multi-disease datasets will increase the system's generalizability to other horticultural crops. When you think about everything, the suggested method shows that AI-powered precision agriculture has a lot of potential. It gives farmers a reliable and automatic tool to manage their crops and spot diseases early on.

VII.REFRENCES

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