DEPARTMENT OF COMPUTER STUDIES

(CS,CA,IT,CT,CS WITH CGS & AIML,DSA,CS WITH CYS)

SUSTAINABLE TRENDS IN COMPUTER SCIENCE

ICSCT - 2025

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HINDUSTHAN EDUCATIONAL AND CHARITABLE TRUST

Hindusthan College of Arts & Science (Autonomous) Coimbatore

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Design and Development Enhanced GRU-Based Plant Disease Detection Using Deep Learning

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ABSTRACT

Crop disease identification plays a pivotal role in ensuring food security and agricultural sustainability. The advent of deep learning has significantly advanced the field of computer vision, providing powerful tools for automated image analysis. In this study, investigation of application with deep learning algorithms for image segmentation in the context of crop disease identification is carried out. So started to conduct an extensive review with the existing literature, that focus on prominent deep learning architectures such as U-Net, FCN, DeepLab and their variants. The research involved the development of a novel dataset comprising images of both healthy and diseased crops, representing diverse crop types. The labeled dataset facilitates the training and evaluation of the proposed deep learning models. The effectiveness of Convolution Neural Network (CNN) using Gated Recurrent Unit(GRU)incapturing intricate detailsrelevant to crop disease segmentation. Additionally, explorethe impact of transfer learning to leverage pre-trained models on large-scale datasets. Then results try to highlight the potential of transfer learning in enhancing the performance of deep learning models particularly when training data is limited. Furthermore, various comparison of segmentation accuracy with different architectures is developed. Then discuss their strengths and limitations in the context of crop disease identification. Multi-scale information integration and comparative analyses contributes valuable insights into the selection of appropriate architectures for specific agricultural scenarios.

Keywords: CNN, CNN-GRU.deep learning, Image Segmentation.

I. INTRODUCTION

Agriculture, being the cornerstone of global sustenance, faces the constant challenge of ensuring crop health to meet the demands of an ever-growing population. The identification and mitigation of crop diseases are critical components in achieving optimal agricultural productivity. additional methods of disease detection often rely on manual inspection, which is time- consuming and susceptible to human error. The integration of advanced technologies, particularly deep learning, has emerged as a transformative solution to automate and enhancethe accuracy of crop disease identification. This research focuses on the application of deep learning algorithms for image segmentation in the realm of crop disease identification. By delving into state-of-the-art architecture of Convolution Neural Networks (CCN),aims is to advance the understanding of how this model can be tailored to address the unique challenges posed by diverse crop types and diseases. The study not only investigates the segmentation accuracy of these models but also explores the impact of accuracy assessment, a technique proven to enhance performance when training data is limited.

II. DEEPLEARNING

Deep learning, a subset of machine learning, leverages neural network architectures to extract intricate patterns and features from complex datasets. In recent years, these techniques have demonstrated remarkable success in various computer vision tasks, prompting their application in agriculture for crop disease analysis. Image segmentation, a fundamental computer vision task, holds immense potential indelineating regions of interestwithinagricultural images, aiding n the precise identification of diseased crops. To facilitate investigation, a curated comprehensive dataset encompassing images of both healthy and diseased crops across various agricultural settings are persuaded [1].

The dataset serves as a benchmark for training and evaluating the proposed deep learning models. Through rigorous experimentation, seek to elucidate the strengths and limitations of different architectures, providing valuable insights for researchers and practitioners engaged in precision agriculture [2]. As the global demand for food security intensifies, the integration of automated crop disease identification tools becomes imperative. This research contributes to the ongoing discourse on leveraging deep learning for precision agriculture, with a specific focus on image segmentation as a pivotal step towards accurate and efficient crop disease identification [3].The outcomes of this study are poised to catalyze advancements in sustainable farming practices and empower farmers with timely and informed decision-making capabilities [4]. The framework of deep learning model is show in Figure 1.

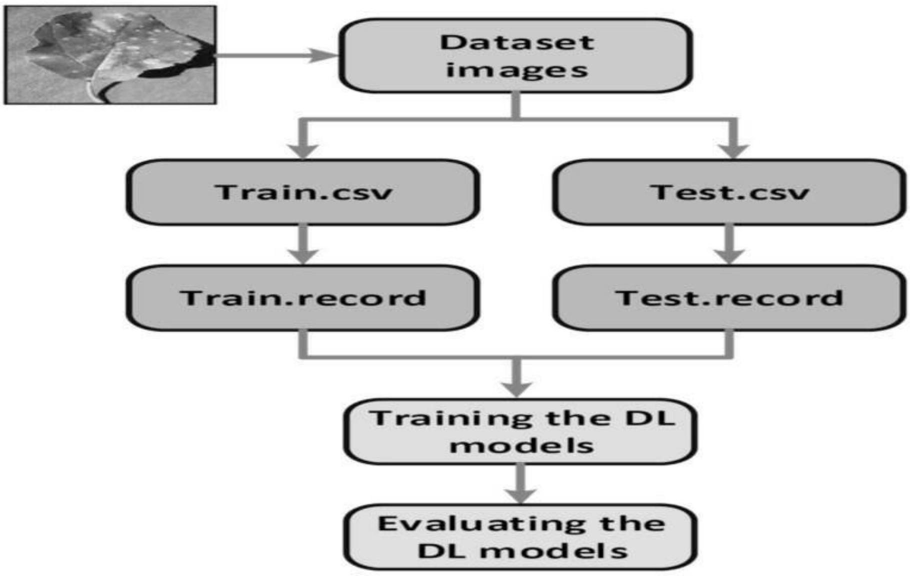


Figure1: Framework of Deep Learning Model

III. PROPOSED CNN-GRU ARCHITECTURE

Identifying plant-leaf diseases using a combination of Convolutional Neural Networks (CNNs) for image processing and Gated Recurrent Units (GRUs) for sequential analysis can be an effective approach. Below is a conceptual outline of how you might structure sucha model.The actual implementation details can vary based on the specification of dataset and task [5]. Input images of plant leaves, each with dimensions (width, height, and channels). Typical preprocessing steps, such as normalization, may be applied. Use convolutional layers to capture spatial features in the input images. Apply filters to identify patterns related to plant diseases. Use activation functions like ReLU to introduce non-linearity. Down sample the spatial dimensions to reduce computational complexity [6].

Algorithm

Step 1: CNN layers consist of convolutional and pooling layers to extract spatial features from the input data.
Step 2: The flatten layer is used to flatten the output of the CNN layers before feeding it into the GRU layer.
Step3: The GRU layer is configured to handle sequential dependencies. return_sequences=Trueensures that it returns the full sequence of outputs for each input sequence.
Step4: Denselayeris used forth efinal prediction.

Max pooling or average pooling can be applied. Create multiple stacks of convolutional layers to extract thier hiearchical features. Each stack captures features at different levels of abstraction. Reshape the output of the last convolutional layer to fit the GRU input. GRUs will process features along the spatial dimension, treating each column as a time step. The hidden states capture contextual information across different spatial regions [7]. Apply up sampling layers to increase the spatial resolution. Concatenate the up sampled features with the corresponding features from the CNN layers. This process allows the model torefine spatial details. Apply additional convolutional layers to further refine the segmented features. Use a convolutional layer with Softmax activation for pixel-wise classification [8]. The number of output channels equals the number of classes (e.g., diseased, healthy).

Image Pre-Processing:

Data Preparation involves in the collection of dataset of plant leaf images containing healthy leaves and leaves affected by various diseases. Organize the dataset into training,validation, and test sets. Build a CNN for image classification [9]. This part of the model will be responsible for extracting features from the leaf images. Use pre-trained models like VGG16, ResNet, or Inception if you have a limited dataset or fine-tune them for your specific task. Remove the final classification layer of the pre- trained model and add a new dense layer for your specific classification task.

Image Segmentation:

Image segmentation is a computer vision task that involves partitioning an image into meaningful segments or regions [3]. The goal is to simplify the representation of an image or make it more meaningful for further analysis. Image segmentation is widely used in various applications, including object recognition, medical image analysis, autonomous vehicles, and more. Proposed architecture ofCNN-GRU for Plant disease detection

Data Augmentation:

Data augmentation is a technique commonly used in machine learning and computer vision to artificially increase the diversity of a training dataset by applying various transformations to the existing data. This helps improve the generalization and robustness of machine learning models, especially in scenarios where the available training data is limited. In the context of image data, data augmentation involves applying transformations to the images, creating variations that still representmeaningful inputs.Apply data augmentation techniques (rotation, flipping, zooming) to artificially increase the size of training dataset and improve model generalization

Disease Detection

Disease detection, especially in the context of computer vision and machine learning, refers to the process of identifying and classifying diseases or abnormalities in various types of data, such as medical images, sensor data, or biological samples [10].

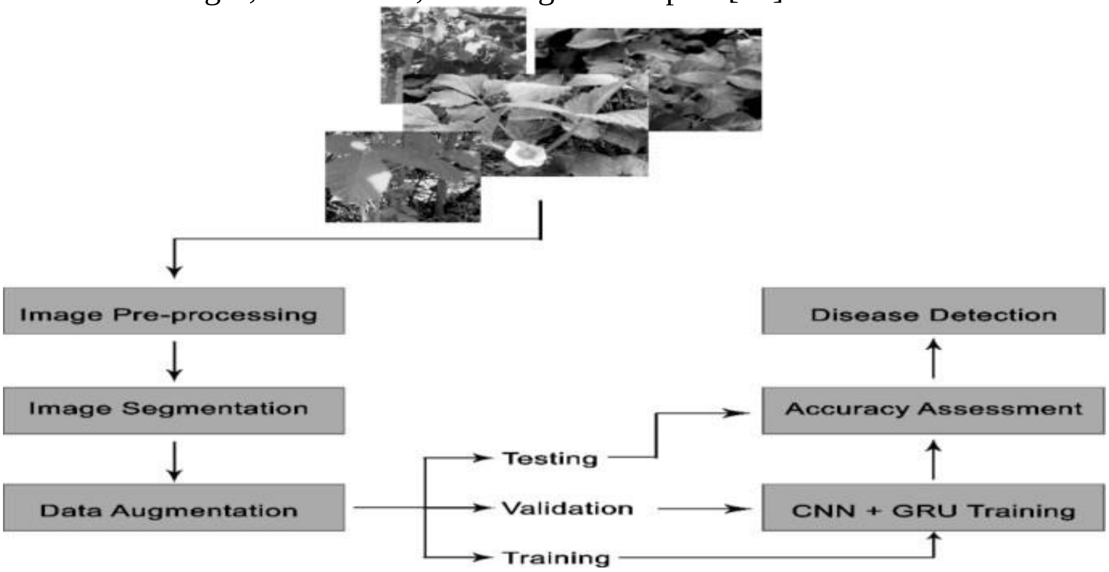


Figure2: Proposed CNN-GRU for Plant disease detection

Accuracy Assessment

Accuracy assessment is a crucial step in evaluating the performance of a machine learning model. It involves measuring how well the model predicts outcomes compared to the actual values. The concept of accuracy is fundamental, but it's important to consider other metrics, especially in scenarios with imbalanced classes or when certain errors are more critical than others.

CNN with GRU for Sequential Analysis

Take the output features from the CNN and feed them into a GRU network. The sequence of features can be considered as a temporalsequence representing the development of the disease over time or as a sequence of different leaves. Add a dense layer on top of the GRU output for final classification. Use softmax for multi-class classification if you have multiple classes (types of diseases).Compile the combined model using an appropriate loss function (e.g., categorical cross entropy) and an optimizer (e.g., Adam).Train the model on your training dataset, including both healthy and diseased leaves. Monitor the performance on the validation set to avoid overfitting.

Training:

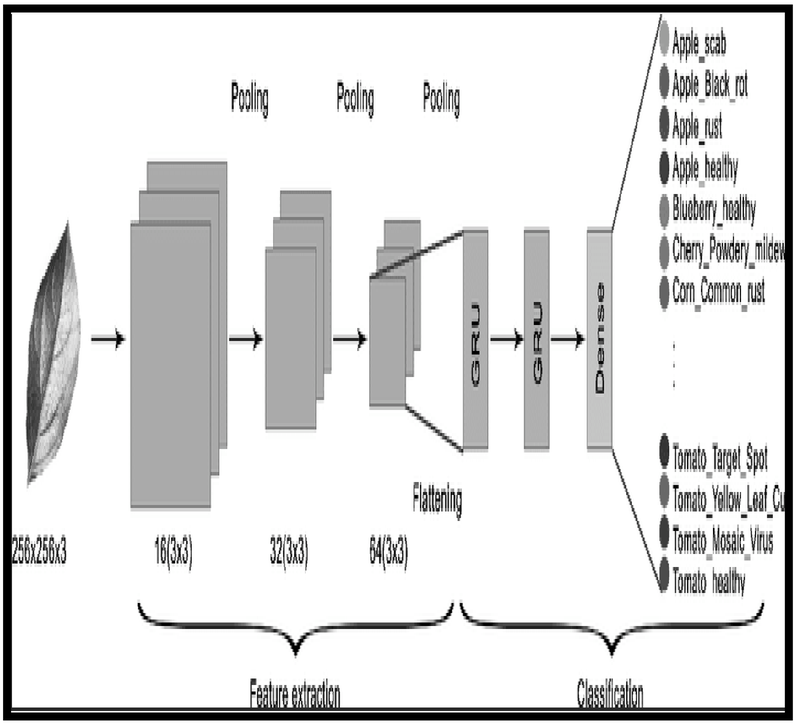
Training a Gated Recurrent Unit (GRU) involves optimizing the model's parameters tominimize a certain loss functionusinga dataset. Training a Gated Recurrent Unit (GRU) involvesoptimizingthemodel'sparametersto a GRU Combining Convolutional Neural Networks (CNNs) with Gated Recurrent Units (GRUs) is a common practice whendealing with sequential data that has both spatial and temporal dependencies. This typeofarchitecture is often referred to as a 2D-CNN-GRU model. Evaluate the trained model on a separate test set to assess its generalization performance [11]. Experiment with hyperparameters such as learning rate, batch size, and the numberof GRU units to optimize the model.

Testing

The CNN part is responsible forcapturing spatial features, while the GRU part handles sequential dependencies. Identifying plant-leaf diseases using a combination of Convolutional Neural Networks (CNNs) for image processing and Gated Recurrent Units (GRUs) for sequential analysis can be an effective approach Minimizea certain loss function using a dataset. Here's a general overview of the steps involved in training [12]. Below is a conceptual outline of how you might structure such a model. The actual implementation details can vary based on the specifics of your dataset and task

Model Deployment

If the model performs well, deploy it for real- world plant-leaf disease identification. When identifying plant-leaf diseases using a combination of Convolutional Neural Networks (CNNs) for image processing and Gated Recurrent Units(GRUs) for sequential analysis, various measurements and metricscan be used to evaluate the performance of the model.



IV. EXPERIMENTALRESULTS

Consider metrics that take into account both image and sequential information. This might involve combining the predictions from the CNN and GRU components in a meaningful way. Techniquessuch as attention mechanisms in the GRU can help to understandwhichpartsofthesequencearemost important for making predictions. Three indices, including overall accuracy, precision, F1 Score and recall, as calculated in Equations (1)–(4), were measured to evaluate the performance of models. Performance of theProposed CNN- GRU model-based framework as shown in Figure 3for Plant diseasehas been evaluated using the parameters namely Accuracy, Precision, F1 Score and Recall are as follows:

Accuracy

The accuracy of the overall model can be measured at the sequence level, considering the entire sequence of predictions, considering both the CNN and GRU components. Accuracy is referred as closeness ofa calculated value to an actual value. Precision value does not dependent on accuracy and is given by

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision

Precision measures the accuracy of disease predictions, and recall measures the ability to capture all instances of disease. Precision measurestheaccuracy ofpositive predictions. It is the ratio of true positive predictions tothe sum of true positives and false positives.

$\text{Precision}=TP/(TP+FP)(2)$

Recall (Sensitivity)

Recall measures the ability of the model to capture all the relevant instances. It is the ratio of true positive predictions to the sum of true positives and false negatives.

$\text{Recall}=TP/(TP+FN)\text{Recall}=TP/(TP+FN)(3)$

F1Score

F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall.F1 Score provides a way to merge both precision and recall into just a single measure that captures TP and TN properties. This is the harmonic mean of the two fractions which is given by

$\text{F1Score}=2T * \quad TP+TN/TN+FP+FN(4)$

Confusion Matrix

A Confusion matrix shows the number of true positives, true negatives, false positives, and false negatives. It provides a detailed viewof the model's performance. Useful for binary classification tasks that illustrates the trade-off between parameters. If data involves a time component, analyze the performance of the modelover time. This isparticularlyrelevantfor diseases that evolve over the course ofthe plant's growth. Choose the evaluation metrics that are most relevant to your specific problem andtakeintoaccountthecharacteristics of dataset. Additionally, it's beneficial to use a combination of these metrics to obtain a comprehensive understanding of your model's performance.The confusion matrices are shown in4. In calculation I, although GRU has the lowest number of true predictions for healthy quadrants, it has more true predictions for diseased quadrants than the other two methods.FortheFCDNN,the opposite isthecase, since230 quadrants were classified as healthy and only 10 quadrants were classified as diseased. The reason is that the FCDNN is more likely to predict samples as healthy. In calculation II, GRU made more true predictions for healthy quadrants. In calculation III, Both GRU and XGBoost classified 105 healthy quadrants correctly; however, GRU had more true predictions for diseased quadrants than XGBoost. In calculationIV, the performance of GRU was similar to that of XGBoost; the difference was only one healthy quadrant. The FCDNN did not perform well in the classification of healthy quadrants. In conclusion, thecalculationresultsshowthatprediction accuracy can be improved by using a sequence-based model, i.e., GRU, with time- series imagery.Besides accuracy, the GRU-based method also achieved greater precision detection in all calculation scenarios, as compared to the XGBoost and FCDNN methods. In all calculation scenarios, the GRU-based method outperformed XGBoost and the FCDNN in predictionaccuracy.AlthoughXGBoostandthe FCDNNareverypowerfulmethods,theydonot incorporatetime-basedinformation.Fromabove confusion matrix, it is found that reflectance values were lower for healthy quadrants than diseased quadrants.

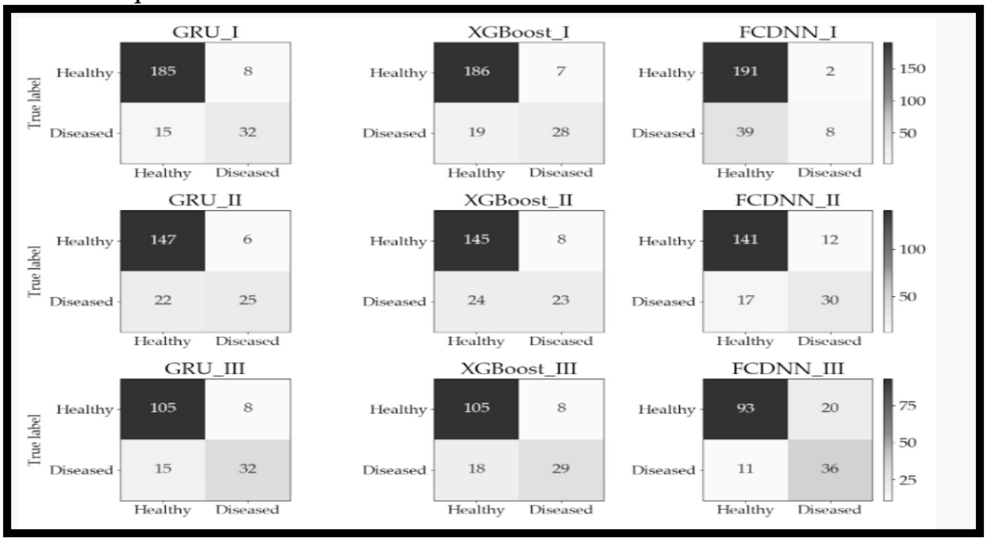


Figure4: Confusionmatrixofthetesting dataset

Moreover,this pattern became clearer near the endofthecropping season, which indicates that incorporating time-based information for satellite images can add information to the dataanalysis.

V. CONCLUSION

The model is tested with apple,blueberry,cherry, corn and tomato leaves. Thedatasetundergoesimage segmentation with data augmentation. Various investigations of machine learning and deeplearning models are carried out and optimally developeda hybridmodelwhichcombines CNN with GRU.The proposed Enhanced GRU-Based Plant Disease Detection System outperforms traditional CNN-based models by capturing sequential feature dependencies. The model is lightweight and suitable for real-time applications.

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