A Research Investigation on Conventional Neural Network-Based Disease Detection Techniques for Sugarcane Plants

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Abstract: In the current times, the number of viruses and infections in the sugarcane plants is widespread. If we want to properly correct these infections, we need to use artificial intelligence such as CNN and RNN. Therefore, in this study, how to prevent the disease in sugarcane using the CNN and RNN system is taken as a test. This model is trained on a diverse dataset of automatic diagnosis images, with a focus on addressing the inherent class in detection. The neural network architecture is designed to capture intricate patterns indicative of sugarcane manifestations in automatic diagnosis images. Through an iterative training process, the model learns to discern subtle features associated with automatic diagnosis, achieving remarkable accuracy. The experimental results confirm the efficacy of our proposed methodology. It explores the many CNN architectures used for plant disease detection, including AlexNet, VGGNet, ResNet, InceptionNet, and DenseNet, as well as their pros and limitations. The survey also discusses the importance of RNNs in plant disease detection, specifically in time-series data analysis, where RNNs have been shown to be useful in forecasting the spread of plant diseases over time. This report also provides a successful outcome for researchers working on the creation of a recognition system for sugarcane diseases.

Keywords: convolutional neural networks (cnn), recurrent neural networks (rnn), Sugarcane plants disease detection Accuracy, Genetic algorithm

Introduction

Sugarcane, a vital crop for the global sugar industry, is susceptible to various diseases that can significantly impact yield and quality. Early detection of these diseases is crucial for effective disease management and crop protection. In recent years, machine learning techniques, particularly neural networks, have shown promise in automating the detection of plant diseases. This study aims to compare the performance of two popular neural network architectures, namely Conventional Neural Network (CNN) and Recurrent Neural Network (RNN), in the context of sugarcane disease detection.

As a member of the Poaceae family of grasses, sugarcane is used to produce white sugar, jaggery, and other by products like molasses and bagasse due to its high sucrose content. On the other hand, a diseased sugarcane plant must be identified quickly because it is useless. A new framework for deep learning. This study suggests a method for determining if a sugarcane plant is infected or not by examining its leaves, stem, colour, and other characteristics. Three scenarios Inception v3, VGG-16, and VGG-19—based on several feature extractors are included in the study. These are the models used to train different classifiers. Deep learning methods such neural networks and hybrid AdaBoost are contrasted with state-of-the-art algorithms (SVM, SGD, ANN, naive Bayes, KNN, and logistic regression).

1. GENETIC ALGORITHMS

Genetic algorithms are based on biological principles. It gains knowledge from Darwin's evolutionary theory. Natural selection, according to Darwin's theory, selects the fittest individuals and produces offspring. These people's attributes are passed down to future generations. If the parents are fitter, their children will be fitter and have a better chance of survival. This concept is passed down to genetic algorithms. They can be applied to optimize and search difficulties Genetic algorithms are used to evolve candidate solutions in order to produce better ones. The purpose of a search space is to discover the best solution among a set of solutions. This is analogous to determining the fittest individual in a group. Genetic algorithms start with a population of randomly produced solutions.

Genetic algorithms are simple yet effective. They have been applied on various research problems such as dynamic channel-assignment problems [1], deep learning hyper parameter optimizations [2] [3], neural network weight optimizations [4] [5] and so on. Many issues have been solved using genetic algorithms with varying chromosome lengths [6] [7]

1.1 Deep learning using Genetic Algorithms

The steps of our hyper parameter optimization method are as follows:

1. Initialize the number of population’s p and generation’s g according to user input.
2. Create the initial population. Each individual in the population has randomized hyper parameters. The size of the population is p as specified by the user.
3. Evaluate the fitness of each individual in the current generation. The fitness is the accuracy of the individual on the validation dataset.
4. Sort individuals based on their fitness value, from high to low.
5. Select the fittest individuals. Select a subset of the population with the highest fitness values and allow them to live into the following generation. It is possible to manually adjust this survival rate's percentage.
6. Allow some less fit individuals to survive. Give the remaining members of the current population a slim probability of surviving into the upcoming generation.
7. Randomly mutate some individuals in the next generation. The mutation rate is manually configured. If an individual is chosen to mutate, one of its hyper parameter’s value will be changed.
8. Produce new individuals. Choose two people at random to be the parents from the following population, then carry out a crossover operation to create a child. Each hyper parameter in the child is randomly set to be one of its parent’s hyper parameter values. Until there are p people in the following generation, repeatedly perform the crossover procedure on several random individuals. Now the next generation becomes the current generation.
9. Repeat Step 3 - 8 until the number of generations has reached g.

Choose the best individual from the present population.

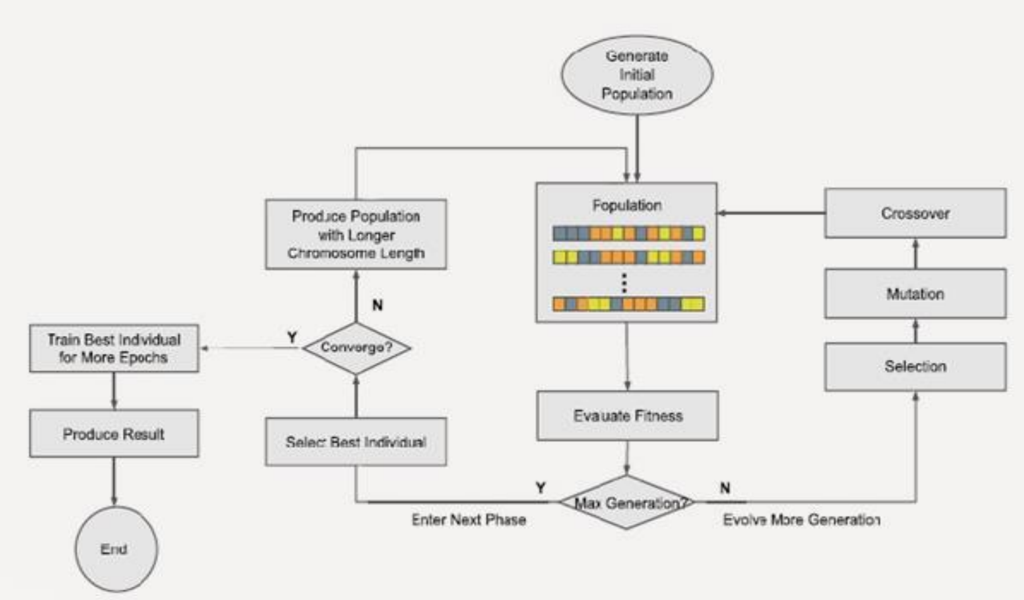


Fig *1. Genetic Algorithms Formation*

10. Produce population with longer chromosome length. For each individual of the population, one part of the chromosome is from the best individual in Step 10, the other part is randomly generated.

11. Repeat step 9 - 11 until convergence.

12. Select the best individual and train for more epochs until convergence.

2. Methodology

2.1. Process Pipeline

The creation of a process pipeline with five major components: acquisition, pre-processing, labelling, DL architecture, and prediction for WLD detection.

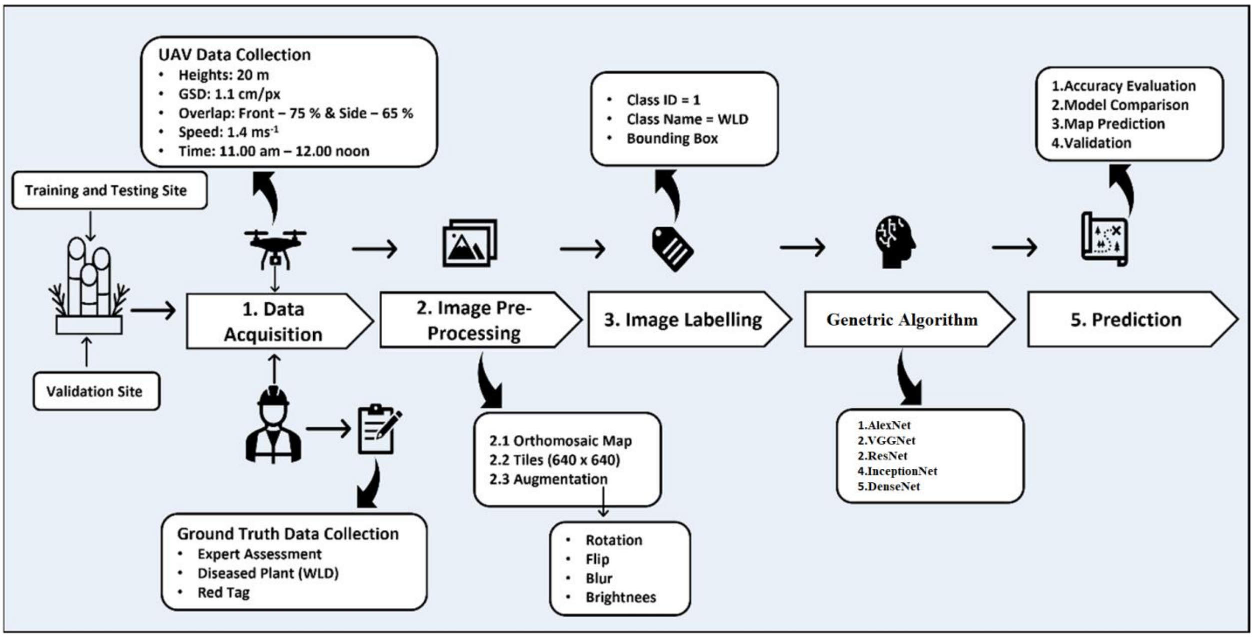


Fig 3. Essential elements of the suggested approach for employing unmanned aerial vehicles to identify WLD.

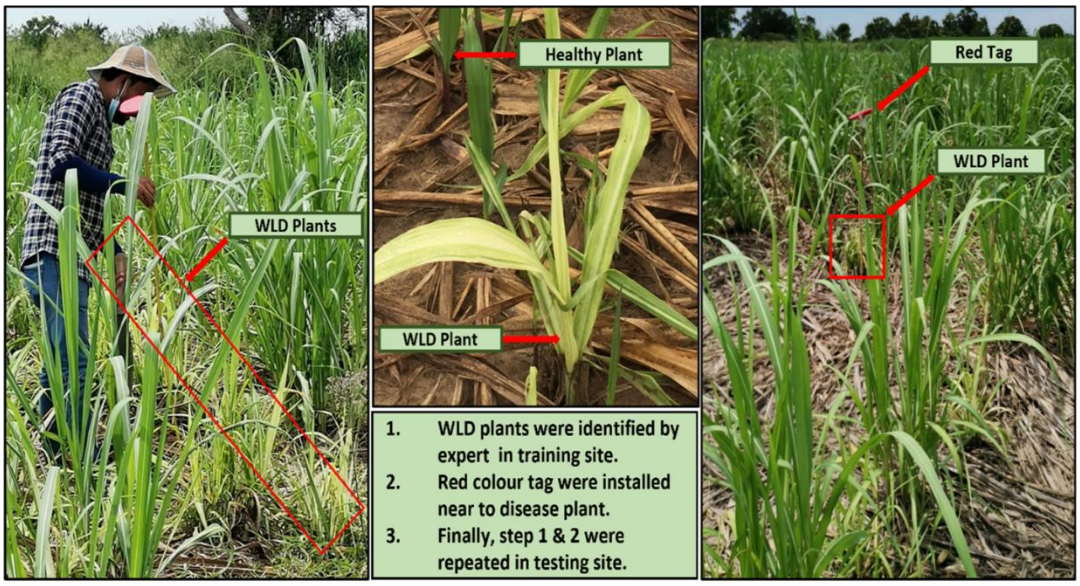
2.2. Study Area

Fig 2. Map Villupuram District

The study area is administratively bounded by Kanchipuram district in the north and north east, Tiruvannamalai district in northwest. Alagramam Village, Kooteripattu block, Mailam Block, Rettanai Block and Gingee Block of Villupuram District.

3. Ground Truth Data Collection:

Before gathering UAV footage, agronomists examined and recognized WLD-infected plants as ground truth [8]. As shown in Figure 3, the red colour tags were installed close to the plants with WLD to ensure that no shadowing or reflectance interfered with the plant imagery gathering, as validated by the field specialists. Infected plants were detected by the emergence of pure white leaves with reduced growth [9].



1. WLD plants were identified by expert in training site.
2. Red colour tag were installed near to disease plant.
3. Finally, step 1 & 2 were repeated in testing site.

Fig 4. Ground truth procedure in the examined sugarcane field.

4. Discussion

while the Genetic Algorithm exhibits higher accuracy, the United Model demonstrates superior precision and recall. The choice between the two models depends on the specific requirements and trade-offs inherent in the application domain. Further analysis and exploration of performance improvement strategies can provide valuable insights for decision-making and model refinement.

5. Comparative Study

Based on the provided data on the accuracy, precision score, and recall score of two models (Genetic Algorithm and United Model), we can make the following comparative analysis:

Accuracy:
Genetic Algorithm: 98.1%
United Model: 97%
The Genetic Algorithm model has a slightly higher accuracy compared to the United model.

Precision Score:
Genetic Algorithm: 97%
United Model : 99%
In terms of precision, the United Model outperforms the Genetic Algorithm model. This implies that, in contrast to the Genetic Algorithm model, the United Model has a higher probability of being accurate when it predicts a favourable outcome.

Recall Score:
Genetic Algorithm: 45%
United Model: 67%
The United Model also has a higher recall score compared to the Genetic Algorithm model. This implies that the United Model is better at identifying true positives out of all actual positives compared to the Genetic Algorithm model.

Overall, if we consider precision and recall along with accuracy, the United Model seems to outperform the Genetic Algorithm model. However, The particular needs and goals of the task at hand eventually determine which of the two approaches is best.

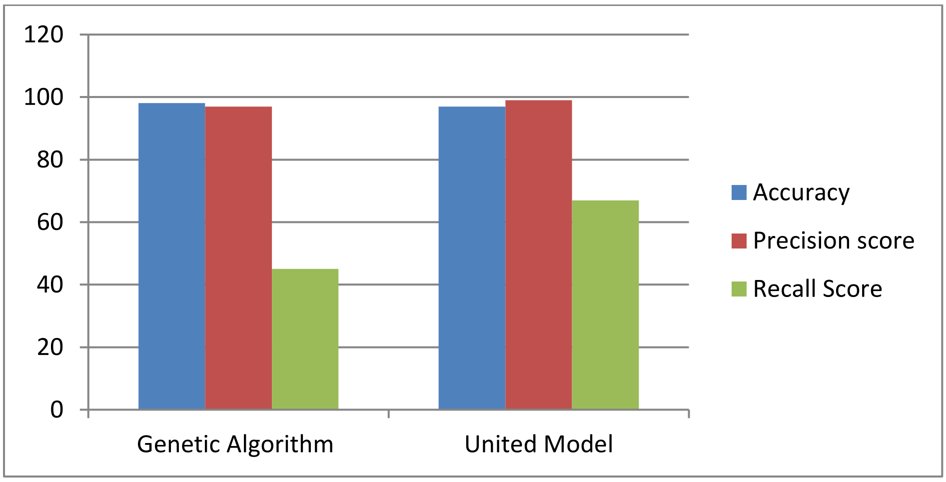


Fig 5. Experimental Results

	Accuracy	Precision score	Recall Score
Genetic Algorithm	98.1	97	45
United Model	97	99	67

Table 1: comparative Analysis

6. Conclusion

Finally, this comprehensive analysis summarizes recent improvements in automated plant disease identification and diagnosis using image-processing algorithms based on CNNs and RNNs. It discusses the field's major challenges and opportunities, as well as a road map for future research in this area. This comprehensive study aims to provide academics, practitioners, and stakeholders in the field of plant pathology with a thorough understanding of how automated image processing techniques such as CNN and RNN have transformed plant disease detection and diagnosis. It investigates the existing state of the art, issues, and future development opportunities, paving the way for improved agricultural practices and sustainable crop management. In this detailed review, we looked into the revolution in plant disease identification and diagnosis using automated image analysis.

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