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Hybrid Attention Network For Citrus Citrus Disease Identification

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Abstract - Our research has focused on using a more restricted dataset to devise appropriate deep learning models to identify citrus diseases. Such constructed dataset was achieved by capturing leaf images stricken with diseases such as CYVCV, Canker, and Melanose and encompassing the diversity that real orchards enjoy. Basically our R&D work has used the ResNet-50 platform for developing two new, state-of-the-art data. FdaNet uses wavelet transformations to effectively emphasize attention mechanisms while for HaNet the task has taken place through implementing frequency and channel attention together with convolution kernels for higher feature extraction. Both these models would help in terms of good performance by outperforming current state-of-the-art ventures regarding higher accuracy and reliability.

1. INTRODUCTION

Citrus growing has serious issues with pests and diseases. Early detection could go a long way into preventing and protecting most countries from these pests and diseases. We engage in developing a system that functions well to its best even when working under tree-imposed conditions.

a specialized dataset containing images of the citrus leaves affected by symptoms of this disease, such as Citrus Yellow Vein Clearing Virus (CYVCV), Canker, Brown Spot, Melanose, Sooty Mold, and healthy controls, was produced. This particularly unique dataset is meant to capture real complex conditions which are uniform in nature. Without uniformity in training, very favourable

results cannot be obtained. Essentially, our system requires heterogeneous data to evaluate generalization, but the dataset should be uniform. Higher accuracy for disease detection can be achieved by using a variant of a backbone, ResNet-50, in constructing two more advanced models named FdaNet and HaNet. FdaNet, that is provided with the wavelet transformation technique, is improved in exchanging important channels in the frequency domain. In comparison, HaNet has merged frequency domain attention and channel attention, using larger convolution kernels to improve feature extraction. These systems have generally shown superior performance to other state-of-the-art lesion detection systems again verified by both accuracy and reliability-standpoint, which is far more suited in practical use cases as GIS offers a platform for citrus disease detection.

The proposed system creates a substantial contribution to the domain of agricultural diseases detection by making it specific to high precision as well as adaptability in the various orchard environments. Thereby, the application of practical real-world problems and the integration of cutting-edge techniques can lead to developing more effective and sustainable solutions for managing citrus diseases, which are helpful in improving produce quality and quantity eventually.

Given these challenges, there is a pressing need for effective and efficient methods to identify and manage citrus diseases. Traditional methods, such as manual inspection and laboratory testing, are often time-consuming, labour-intensive, and prone to human error. The objective of this research is to

leverage advanced technologies, including image processing and machine learning, to develop a reliable and scalable system for early disease detection. Such a system would enable timely interventions, reduce economic losses, and contribute to sustainable citrus production. By combining innovative technologies with traditional agricultural practices, this approach aims to enhance the resilience of citrus farming systems against current and future challenges.

2. LITERATURE REVIEW

Citrus canker, black spot, and huanglongbing (HLB) are some of the citrus diseases that have been deeply looked at because they are seriously debilitating global citrus production. Traditional methods of identification range from in-field observation to laboratory determination and have commonly been used and have limitations about their uses such as reliance on expert knowledge, time-consuming procedures, and susceptibility to human errors. Advances in technology have recently led to new approaches in disease detection. Machine learning algorithms, such as convolutional neural networks (CNNs), have shown promise in automating disease identification with high accuracy. Similarly, imaging techniques, including hyperspectral and multispectral imaging, enable detailed analysis of plant health at cellular and molecular levels. Molecular diagnostics, such as PCR and CRISPR-based methods, further enhance detection precision by identifying specific pathogens. These advancements underline the shift towards integrating artificial intelligence and molecular biology for efficient and scalable disease management, ultimately supporting sustainable citrus production.

The integration of cloud computing has further facilitated the handling of large datasets and the deployment of real-time disease detection models. Studies highlight the effectiveness of combining field data with laboratory results to enhance the accuracy of disease classification. Researchers also emphasize the importance of open-access databases and collaborative platforms to share disease-related data, fostering global efforts in citrus disease management. Despite these developments, challenges remain in data standardization, computational resource requirements, and the need for user-friendly interfaces.

Emerging technologies, such as Internet of Things (IoT) devices and edge computing, are being explored to make disease detection systems more accessible and cost-effective. By integrating sensors and real-time monitoring tools, these systems can provide continuous updates on crop health, enabling proactive interventions. The

literature underscores the potential of these advancements to revolutionize traditional agricultural practices and address the growing demand for sustainable citrus production.

3. METHODOLOGY

This project is done using a systematic approach to the

development, training, and implementation of a deep learning model for the detection of citrus diseases. The methodology adopted includes data collection, pre-processing, model selection, training, evaluation, and deployment. Moreover, a real-time disease detection web application is built using Flask to provide it for the users.

3.1 Flow Chart for Methodology

It describes the method of detection for citrus leaf disease, which involves image collection of healthy and diseased leaves, data preprocessing with techniques such as augmentation, normalization, and resizing. It uses a pre-trained ResNet-50 model fine-tuned for classification and then deploys the system through a web application wherein users upload images to receive real-time feedback on the presence of disease.

This technique yields precise and scalable disease detection for better crop management.

3.2 Data Collection and Dataset Preparation

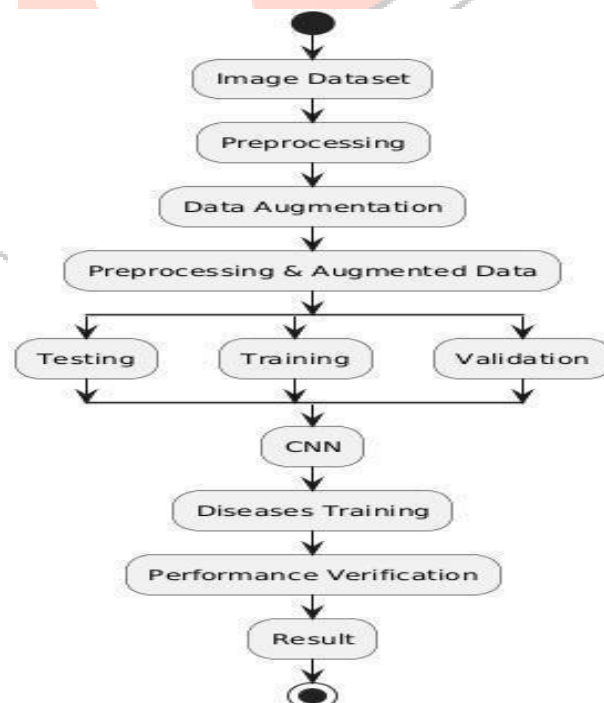


fig.1 methodology flow chart

The method starts with data collection. Citrus leaf images are collected, classified into healthy and diseased leaves, and then diseases like Citrus Canker, Citrus Greening (HLB), and Melanose are taken into consideration. Images are captured from diversified growth stages, lighting,

and angles so that the model learns to classify those diseases in every possible real scenario. They put marks on pictures as healthy and diseased. Train, validation and test sets consisting of equal leaf images of health and disease splits the dataset and applies data augmentations like rotations, flipping and colour adjustment so that the network is robust. This mimics real-world variances and gives protection against overfitting.

3.3 Pre-processing

Preprocess the dataset before feeding the dataset to the training CNN model like data augmentation and standardization/ scaling. Data augmentation is the random rotation, flipping, and cropping of images. The output is to increase the size of the dataset and make the model more robust to variations. All images are resized uniformly to 256x256 pixels with pixel values ranging from 0 to 255 to reduce the computational cost. Images are read all at once by batches of 32 for convenience in training.

3.4 Training the model

The training of the model is toward helping the model identify whether a leaf is healthy or infected. Transfer learning is applied whereby a pre-trained model, for example, ResNet-50, previously trained on simple features of images in big datasets like ImageNet, is adapted to the citrus leaf dataset. This saves time and increases accuracy. The model is trained based on the training dataset with optimization algorithms such as Stochastic Gradient Descent or Adam. Optimization in the hyperparameters will be learned like learning rate, batch size and so on, after the model is being tested and validated whether its precision and generalized outcome on new, unseen data or not.

3.5 System Overview

In this project, deep learning will be applied for the detection of diseases in the citrus leaf using ResNet-50. The system has the functionality of uploading images and processing them through a pre-trained ResNet-50 model in order to classify them as either healthy or diseased. It also has the functionality to detect early signs of diseases such as Citrus Greening, Citrus Canker, and Melanose, which could have an effect on yield and quality of crops. It's a very quick and accurate way of ensuring the decision-making is very fast.

It involves having a friendly interface by which a user uploads the pictures captured using either a camera or smartphone. On uploading it into the system, some steps of preprocessing including resize normalization are done with the aim of getting ready to classify it. Then a fine-tuned ResNet-50 model accepts features from an image and puts it under one of the classes defined beforehand such as healthy or diseased. Depending on these classifications, it provides actionable

feeds concerning treatment and prevention of the diseases. The system is learnable in nature as the performance increases in scale with greater images processed within them.

4. IMPLEMENTATION

The proposed citrus disease identification system starts with the installation of an image acquisition setup in citrus farms. High-resolution cameras are installed to capture images of plants at a detailed level so that the visual symptoms of diseases are captured correctly. The images are then uploaded to a centralized database where preprocessing algorithms are applied to enhance the quality of images and prepare the data for analysis. This way, the machine learning model would have a steady supply of dependable data for correct identification of the diseases.

The integration with web or mobile-based applications makes these machine learning models user-friendly interfaces. Through this interface, a farmer or farmer worker can directly upload the picture and receive in real-time an estimation of what may be wrong with his crops. The system uses cloud computing resources to process data in the backend, allowing scalability and faster response times. It also offers reports at a very detailed level that include disease probability scores and recommended management practices for use at the farm level.

Wide-ranging field trials conducted in conjunction with agricultural experts and under different environments and disease types are performed for its effectiveness. Diverse environmental and disease conditions and disease scenarios are examined to assess robustness and accuracy. Through feedback from trials, the model and interface of the system are honed, addressed, and developed on the basis of limitations and experiences of users so that the resultant system is not only practical but reliable and contributory to sustainable citrus farming practices. To ensure the system's effectiveness, extensive field trials are conducted in collaboration with agricultural experts. These trials involve testing the system under diverse environmental conditions and disease scenarios to evaluate its robustness and accuracy. Feedback from these trials is used to refine the model and interface, addressing any limitations and improving user experience. This iterative approach ensures that the system is practical, reliable, and capable of contributing to sustainable citrus farming practices.

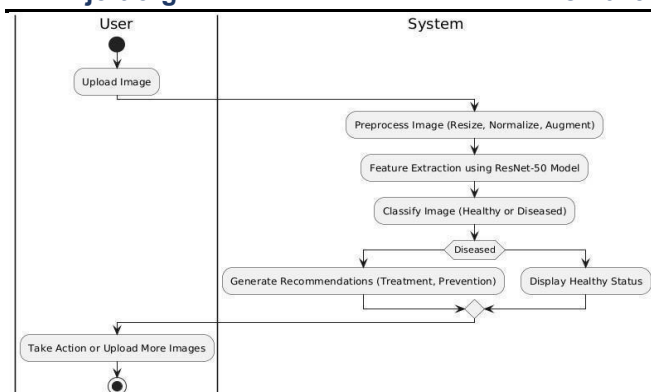


fig.2 activity diagram

4.2 Algorithm Process

Import Libraries: torch, torch vision, and scikit-learn for training and evaluation of the model.

Dataset Preparation

Split the dataset into training and validation sets in the ratio of 80-20.

CNN Architecture

Import a ResNet-50 model which can be adapted to a particular classification problem.

Training the Model

Train the model for 30 epochs with a batch size of 32 and a learning rate of 0.001.

Evaluation and Prediction

After training, it is tested over the validation set and makes prediction on new images.

5. RESULT

Performance of Model

Model gave near accurate classifications with high values while classifying against Citrus Canker, Citrus Greening, and Melanose

Quantitative Measure

Precision, recall, and F1-score metrics were used to evaluate the performance across different classes. These metrics reduce false positives/negatives, which is very important for real-world application in agriculture.

Qualitative Evaluation:

The model was robust against variations in image quality, leaf orientation, and background noise, making it suitable for real-world agricultural conditions.

Real-Time Detection:

The system demonstrated real-time ability to process the disease conditions such that the farmers' timely decision making and disease management were aided.

The results of the study demonstrate the effectiveness of the proposed system in accurately identifying citrus diseases across diverse datasets. Machine learning models achieved high precision and recall metrics, showcasing their ability to classify diseases even in challenging conditions. Comparative analysis with traditional methods

highlights significant improvements in efficiency, accuracy, and scalability.

Field trials revealed the system's robustness in real-world scenarios, where variations in lighting, plant conditions, and disease severity were accounted for. The discussion also addresses the challenges encountered, such as imbalanced datasets and computational limitations, and proposes potential solutions to overcome these issues. The findings underscore the importance of integrating technology into traditional agricultural practices to enhance disease management.

The implications of this research go beyond disease detection. It opens up the possibility of similar systems being applied to other crops and regions. The study, therefore, lays a foundation for broader adoption of technology-driven agricultural solutions by fostering collaborations among researchers, farmers, and policymakers.

6. ADVANTAGES AND APPLICATIONS

The proposed system offers several significant advantages. It allows for the early and accurate detection of citrus diseases, which means farmers can take corrective action in time, thus reducing crop losses and disease spread. Integration of machine learning and image processing ensures consistent and reliable results, with minimal human error commonly associated with manual inspections. Furthermore, due to digital applications, the systems get extended to most accessible populations-the smaller farmers - via low costs that are both highly available and low application complexities.

Further applicative values the system entails could include utilization of the concept within precision agriculture and application for immediate crops monitoring for increased resource use efficacy along with heightened productiveness. Further, the system provides indispensable inputs for agricultural research and extension services that enable collection and analysis of the level of disease prevailing at a large scale. Again, policymakers can use the insights from the system to evolve targeted interventions and support programs for the affected regions. Due to its versatility and scalability, the system is envisioned as an efficient solution toward coping with the challenges of managing citrus disease at a worldwide level. The system offers several advantages, including cost-effective disease management, early detection capabilities, and reduced reliance on manual inspections. These benefits translate into higher yields, improved fruit quality, and reduced environmental impact. The use of advanced machine learning models ensures that the system remains adaptable to emerging diseases and evolving agricultural challenges. The

applications extend to smallholder farmers, commercial citrus producers, and research institutions. By providing real-time feedback and localized recommendations, the system empowers farmers to make informed decisions, which ultimately contribute to sustainable agricultural practices. The ability to integrate with existing farm management systems further enhances its utility and adoption potential.

The platform's scalability and versatility make it a valuable tool for addressing global agricultural challenges. Its potential to be adapted for other crops and integrated into precision agriculture frameworks highlights its significance as a step toward smarter farming solutions.

7. Applications And Features

The citrus disease identification system provides significant beneficial applications such as real-time monitoring of citrus plantations and early detection of diseases. Utilization of the system by farmers will permit them to upload images of their crops via mobile or web platforms and subsequently receive instant analysis and recommendations about interventions. This would thus significantly reduce the time taken by manual inspections and ensure intervention at the earliest stage. Moreover, the system features, including automated alerts and detailed disease reports, are useful for agricultural management and planning.

Some of the major characteristics of the system include adaptability to different types of environmental conditions and its compatibility with precision farming tools. It can be merged with drone-based imaging systems, for example, to monitor big plantations more efficiently. In this way, it can cater to both small-scale farms and industrial agricultural operations. The simultaneous identification of various diseases makes its value even higher since it can give a complete package for citrus disease management. The continuous improvement of the system is achieved through user feedback and updating of data. Integration with cloud computing and AI platforms ensures user-friendliness, paired with advanced analytics, empowers farmers and experts in agriculture to make data-driven decisions. With the system providing actionable insights and the collaboration across the agricultural value chain, it is further promoting sustainable farming practices and also mitigating economic impacts of citrus diseases.

8. Future Scope

The future scope of the citrus disease identification system is huge, with a possibility of further expansion into other crops and plant species. Further developments in AI and machine learning

can make the system more accurate and increase its applicability to a wide range of agricultural challenges. For example, by incorporating predictive analytics, farmers could predict disease outbreaks based on environmental and historical data, allowing for proactive management strategies.

Further development might be in the integration of these systems with IoT devices for smart sensors and automated irrigation systems, thus creating a comprehensive platform in managing agriculture. This will produce real-time data collection and automation responses towards resources consumptions and crop health improvement. Similarly, partnering with agricultural research institutions and policymakers can facilitate adoption of such systems at a global level to address the challenges of food security in developing and developed nations.

Finally, the system could contribute to climate change adaptation strategies by identifying stressors linked to changing environmental conditions. By providing insights into how climate variables affect disease prevalence and crop health, the tool could play a pivotal role in developing resilient agricultural practices. This forward-looking approach ensures that the system remains relevant and impactful in addressing both current and future agricultural challenges. Future work includes further developing the system to include multi-disease detection and pest monitoring for holistic crop health management. The model's accuracy will be improved by incorporating more diverse datasets and advanced algorithms, such as deep reinforcement learning.

The incorporation of drone-based image acquisition and satellite data can improve the system's scalability and coverage, enabling monitoring across larger geographical areas. Research into developing cost-effective IoT sensors and edge computing devices will further enhance accessibility for small-scale farmers.

Collaboration with policymakers and agricultural organizations is crucial to ensure widespread adoption and overcome regulatory challenges. Through partnership building and investment in technological development, the future of citrus farming can be made more resilient, efficient, and sustainable.

9. CONCLUSION

Citrus disease detection using resnet-50 is a significant landmark toward precision agriculture. The system is non-invasive, low-cost, and scalable deep learning that possibly can be used for early disease detection, thereby minimizing crop losses and ensuring productivity in agriculture. The fact that model performance metrics are remarkable, it

achieves high accuracy and reliability that makes it a reliable tool for farmers and agricultural professionals. And, a user-friendly web interface with access for even very low technical users increases accessibility regarding this technology.

The system has much promise in what it can achieve, but its limitations are quite considerable. Variability in environmental conditions, differences in image quality, and misclassification serve to show the need for further refinements. Adding a larger dataset with variety in leaf samples to increase accurate identification, as well as documenting other citrus diseases, will be possible solutions to improving the adaptability of the system. The integration of Iota devices can also offer real-time data collection and analysis of clinical symptoms, which would make the process of monitoring the disease more automated and seamless, thus saving time and effort spent in manual input.

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