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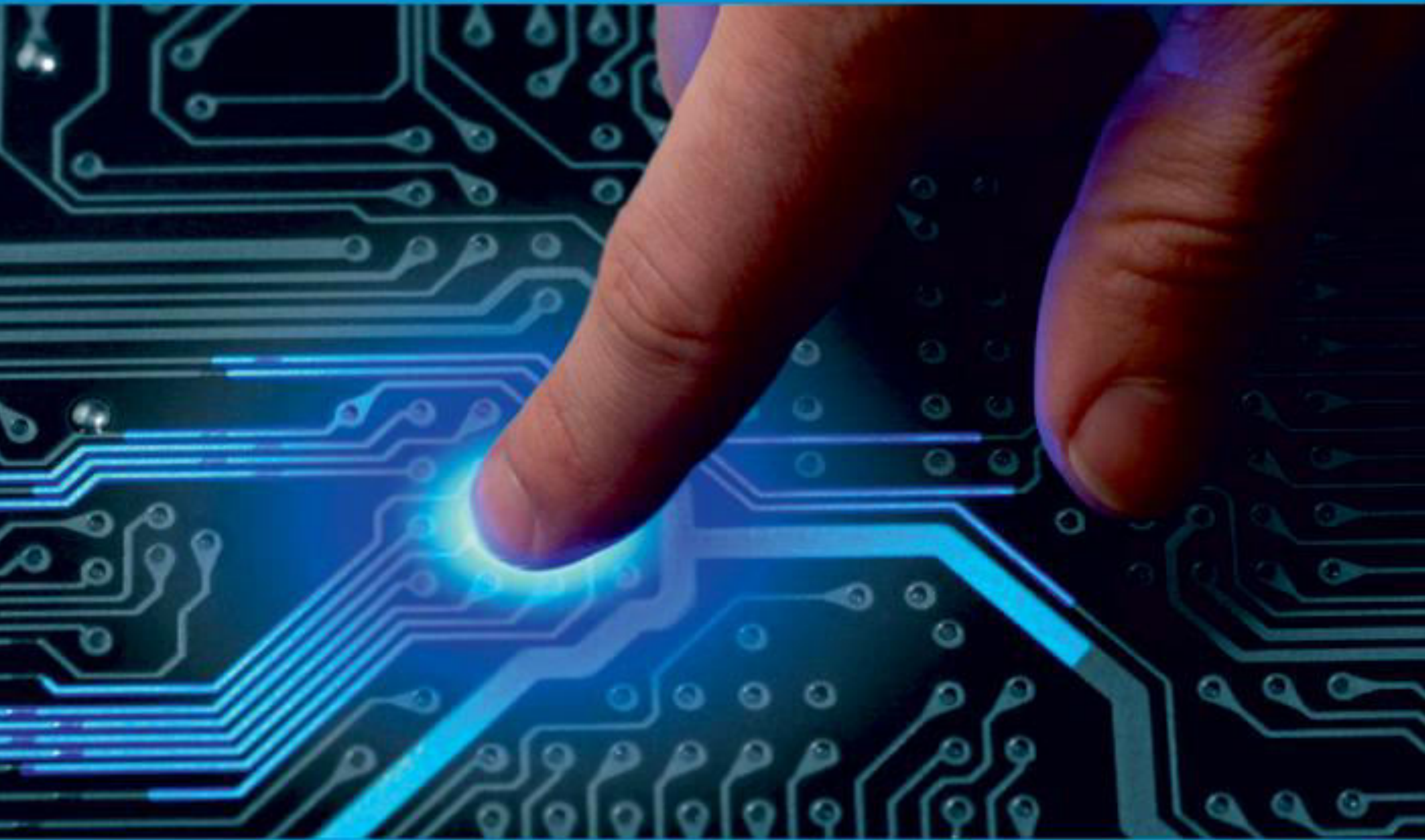

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Edge-Cloud Remote Sensing Data-Based Plant Disease Detection Using Deep Neural Networks with Transfer Learning

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ABSTRACT: The identification and control of plant diseases have become increasingly complex as agricultural lands expand globally. Traditional manual methods of monitoring and diagnosing diseases are not feasible for large-scale farms. The complexity is further heightened by the heterogeneity of data types collected through remote sensing methods, such as images, videos, and sensor readings, which need to be processed in real-time. This paper introduces a novel Edge-Cloud Remote Sensing architecture that utilizes Deep Neural Networks (DNNs) with Transfer Learning to enhance the detection of plant diseases using remote sensing data. The proposed system employs a Fuzzy Deep Convolutional Neural Network (FCDCNN) to process multimodal data collected from both edge nodes and satellite point clouds. Transfer learning allows the sharing of model weights between cloud and edge nodes, thus optimizing performance without requiring frequent retraining. Simulations show that the proposed system achieves a 98% detection accuracy and reduces processing time by 25% compared to existing methods. By distributing tasks between edge and cloud resources, the system is able to process large datasets effectively and improve disease detection performance on vast farmlands.

KEYWORDS: Edge Point Cloud, Fuzzy Deep Neural Networks, Plant Disease Detection, Remote Sensing Data, Transfer Learning

I. INTRODUCTION

The agricultural industry has long relied on manual inspections to monitor crop health, but with the increase in farm size and the development of satellite technology, remote sensing has emerged as a key tool for monitoring plant health. NASA, ESA, and Digital Globe provide a wealth of remote sensing data through satellites that capture images in various wavelengths, such as infrared and thermal bands, which are useful for identifying stressed vegetation. However, the sheer volume of data collected poses significant challenges in terms of processing speed, accuracy, and noise reduction, particularly when scaling for use across vast agricultural lands. This paper presents a hybrid Edge-Cloud Remote Sensing System, designed to overcome the limitations of current remote sensing technologies by combining the strengths of edge nodes and cloud computing. The system integrates Deep Neural Networks (DNNs) with Transfer Learning, enabling efficient sharing of learned knowledge between the cloud and edge devices. The edge nodes handle real-time processing, collecting and processing data close to the plants, while the cloud nodes are responsible for large-scale data analysis using satellite-collected data. The proposed system also incorporates Fuzzy Logic into the FCDCNN model, which improves the handling of noisy and incomplete data and enhances disease detection accuracy.

II. LITERATURE SURVEY

The use of remote sensing technologies for monitoring agricultural health has been extensively explored, with organizations like NASA and ESA providing multispectral data for crop health assessments, including thermal and infrared images useful for detecting stressed vegetation. However, these systems face challenges such as data noise, overwhelming data volumes, and the need for sophisticated processing techniques. For example, Nguyen et al. (2021) employed Convolutional Neural Networks (CNNs) to process hyperspectral images for early plant disease detection, but their approach is computationally intensive and often struggles with real-time deployment.

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Additionally, point cloud segmentation has been investigated, with Li et al. (2022) applying it to classify plant species and identify diseases through 3D models; however, this method is sensitive to noise and requires significant computational resources, making it impractical for real-time field applications. Edge computing presents a more viable solution for real-time monitoring by distributing data processing tasks to edge nodes near the plants. For instance, Shahi et al. (2023) combined UAV-based data collection with edge computing, but their approach was limited to image data and did not integrate multimodal information like sensor readings or video feeds. This paper advances these efforts by proposing a hybrid Edge-Cloud Architecture that efficiently handles multimodal data, enhancing both accuracy and scalability.

III. METHODOLOGY

The proposed Edge-Cloud Remote Sensing Architecture integrates edge nodes for real-time data collection and cloud-based nodes for large-scale processing. This distributed system aims to address the challenges associated with traditional remote sensing methods, particularly in processing large datasets across geographically distributed farmlands. The architecture relies on both satellite point clouds and edge computing nodes to gather data, with a Fuzzy Deep Convolutional Neural Network (FCDCNN) at the core of the processing pipeline.

At the edge level, edge nodes are deployed in close proximity to the agricultural fields. These nodes are responsible for collecting high-resolution images, videos, and numerical data from the plants in real-time. The edge nodes perform initial data processing using deep convolutional neural networks, which are optimized through transfer learning. By utilizing pre-trained weights, the system minimizes the need for resource-intensive training on local edge devices. Once processed, the data is sent to the cloud for further analysis and storage.

The cloud-based satellite point clouds serve as the primary data collection nodes for larger geographical areas. They collect remote sensing data, including multispectral images and thermal data, which are used to monitor plant health and detect potential diseases. The cloud nodes handle the heavy computational tasks associated with training the FCDCNN model on large-scale data. The transfer learning model enables the cloud to share pre-trained weights with the edge nodes, ensuring that the entire system operates efficiently with minimal delays in data processing.

The fuzzy logic component of the FCDCNN model allows for more accurate decision-making in the presence of noisy data. Remote sensing data often contains uncertainties due to environmental factors like weather conditions or sensor limitations. The fuzzy logic system helps mitigate these issues by introducing degrees of certainty into the classification process, reducing the likelihood of false positives in disease detection.

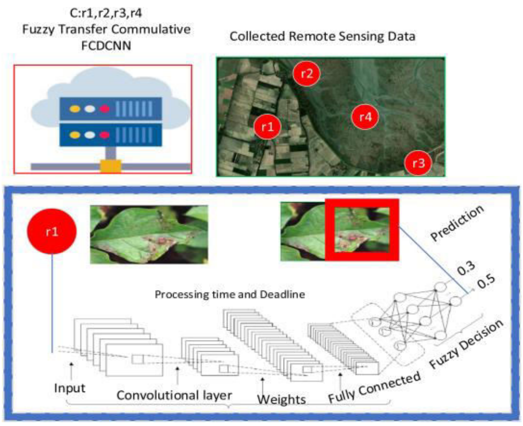

Fig 1. Remote sensing training based on FCDCNN scheme.

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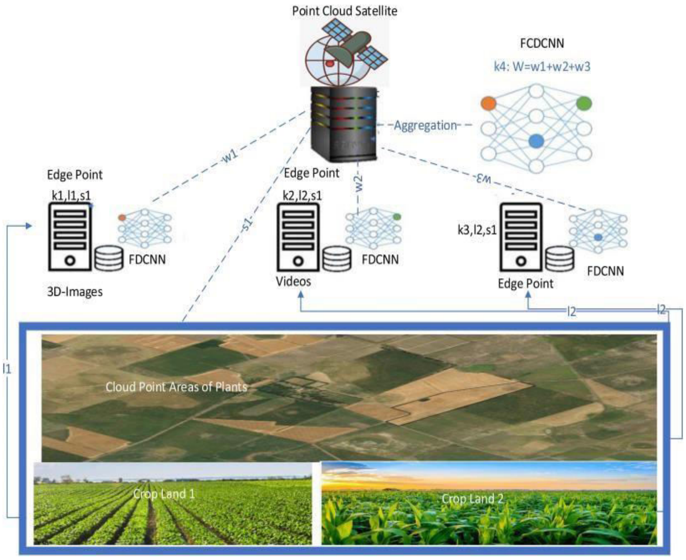

Fig. 2: Edge-Cloud System Architecture

IV. EXPERIMENTAL RESULTS

The Edge-Cloud Remote Sensing System was evaluated using a dataset consisting of various crops, including sugarcane, blueberry, cotton, and cherry. The dataset included multimodal data types such as images, videos, and numeric sensor readings. The system was tested for its ability to detect common plant diseases across these crops, and its performance was compared against traditional models such as RSFDCNN and ESFDCNN.

The results demonstrated significant improvements in both accuracy and processing time. The proposed FCDCNN model achieved an impressive 98% accuracy in detecting plant diseases, outperforming existing methods by a wide margin. In terms of processing time, the system was able to reduce the overall data processing time by 25% compared to traditional deep learning models. This reduction was attributed to the efficient distribution of tasks between edge and cloud nodes, as well as the use of transfer learning, which allowed edge nodes to utilize pre-trained models rather than retraining from scratch.

The system's confusion matrix, which visualized the classification results, showed a high correlation between predicted labels and actual plant health statuses. False positives and false negatives were minimized due to the incorporation of fuzzy logic, which allowed the model to handle noisy data more effectively. The accuracy comparison graph illustrated the performance of the proposed model in relation to other models like RSFDCNN and ESFDCNN, clearly demonstrating the superiority of the FCDCNN model in both accuracy and processing efficiency.

The simulation results also highlighted the system's scalability, as it was able to handle large datasets collected over vast geographical regions without significant delays or loss of accuracy. By utilizing both edge and cloud resources, the system maintained a balance between local processing and large-scale analysis, making it suitable for real-time deployment in diverse agricultural environments.

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Method	Plant	Accuracy	Recall	Precision
FCDCNN	Cotton	98.5	0.98	0.98
RSFDCNN	Cotton	83.5	0.89	0.84
ESFDCNN	Cotton	80	0.85	0.83
FCDCNN	Cherry	92.2	0.91	0.98
RSFDCNN	Cherry	89.5	0.82	0.80
ESFDCNN	Cherry	81	0.83	0.81
FCDCNN	Cherry	98.2	0.98	0.98
RSFDCNN	Cherry	90.5	0.89	0.83
ESFDCNN	Cherry	89	0.88	0.84

Table 1: Ground truth data for the plant disease benchmarks stage with result analysis

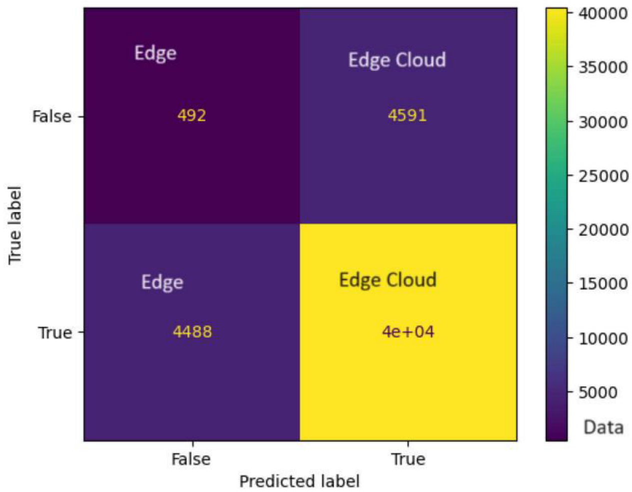

Fig 3: Confusion matrix of training of remote sensing data on transfer learning different edge cloud nodes.

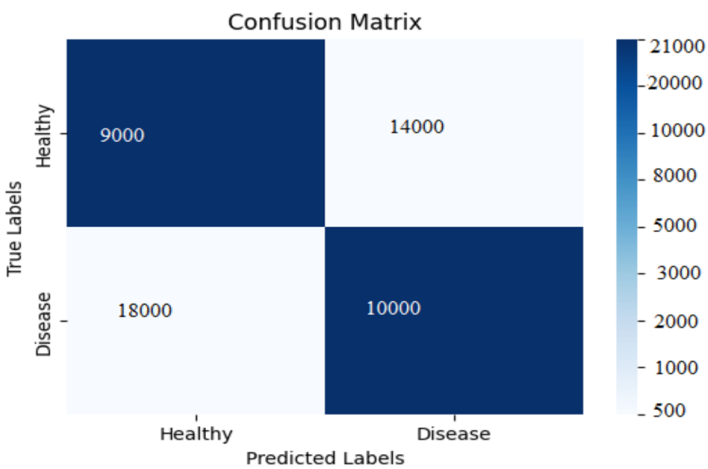

Fig 4: Confusion matrix on trained plant data for healthy and disease detection.

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V. CONCLUSION

This study presents a novel Edge-Cloud Remote Sensing System that combines Deep Neural Networks (DNNs) with Transfer Learning to optimize plant disease detection across large agricultural landscapes. The system's ability to process multimodal data, including images, videos, and numeric values, ensures that it can detect diseases with high accuracy, even in the presence of noisy or incomplete data. The use of fuzzy logic within the FCDCNN model further enhances the system's performance by allowing it to handle uncertainty more effectively. The simulation results demonstrate that the proposed system significantly outperforms existing methods, achieving a 98% accuracy and reducing processing time by 25%. Future work will focus on integrating additional factors, such as the economic impact and processing costs, into the model. Furthermore, additional security measures will be implemented to protect sensitive agricultural data, ensuring that the system can be deployed on a larger scale for real-time monitoring and disease prevention.

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