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Sugarcane Disease Prediction and Integration IOT Sensors using Deep Learning

Anjali. M. Manakoji[1] and Dr. Ajit. S. Gundale[2]
[1-2]Department of Electronics Engineering, Walchand Institute of Technology, Solapur, India
Email: anjalimanakoji@gmail.com, asgundale@witsolapur.org

***Abstract*— In today's environments, A number of diseases brought on by pathogenic bacteria, viruses, and fungi reduce the yield of sugarcane, an economically important crop. The farmers are suffering from different problems like over raining, diseases on crops etc. Some of the new farmers don't understand the management of crops and how to save crops from disease. By identifying disease indicators using datasets of photos of sugarcane leaves. We employed a Convolutional Neural Network (CNN) in this project. To categorize the various illnesses, including rust, mosaic, red rot, smut, and yellow. To classify the different diseases such as smut, red rot, mosaic, yellow and rust. A clever, Internet of Things-integrated deep learning system for predicting sugarcane disease is proposed in this paper.and the system utilizes the data like temperature, soil moisture, humidity and leaf wetness by using and integrating with IOT sensor. To reduce output loss and guarantee sustainable cultivation, these illnesses must be detected early and accurately predicted. This study suggests an integrated approach that uses deep learning models and Internet of Things-based sensor technology to forecast sugarcane diseases. While image sensors take high-resolution pictures of sugarcane leaves, IoT sensors are placed in the field to gather real-time environmental data like temperature, humidity, soil moisture, and leaf wetness. To recognize and classify the collected multimodal data, a hybrid model that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) looks at both visual and environmental features.**

***Keywords*— Sugarcane leaf disease prediction dataset, deep learning, convolutional neural networks (CNN), Integration with IOT sensors.**

I. INTRODUCTION

A highly lucrative crop that is cultivated all over the world, sugarcane serves as the main source of ethanol, sugar, and a variety of other by products. Especially in Solapur district and neighbourhood districts has more sugarcane plantation and sugar industries as compare to other area. In nations like India, Brazil, and Thailand, sugarcane cultivation significantly bolsters the agricultural economy and industrial development. The productivity and quality of sugarcane are frequently jeopardized by various diseases, such as red rot (Colletotrichum falcatum), smut (Sporisorium scitamineum), leaf scald (Xanthomonas albilineans), and mosaic virus infections. Current techniques to recognize infections rely mainly on manual field evaluations completed by agricultural experts, which are time-consuming, difficult, and often subjective. Consequently, there is an urgent requirement for automated, precise, and real-time disease prediction systems to facilitate precision agriculture and sustainable farming methodologies.

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These diseases can result in significant yield reductions if not identified and addressed promptly. Standard disease identification techniques depend significantly on manual field tests, and conducted by agricultural experts, which are laborious, time-consuming, and frequently subjective. Consequently, there exists an urgent requirement for automated, precise, and real-time disease prediction. A major shift in agriculture toward advanced farming systems is being accelerated by the development of Internet of Things (IoT) technologies. IoT-enabled gadgets can constantly track crop and environmental parameters like pH levels, leaf wetness, temperature, humidity, and soil moisture. These real-time data streams provide valuable insights into the crop's growing conditions and disease susceptibility. Conventional techniques for disease identification depend significantly on manual field assessments conducted by agricultural specialists, which are laborious, time-consuming, and frequently subjective. Consequently, there is an urgent requirement for automated, precise, and real-time disease prediction systems to facilitate precision agriculture and sustainable farming methodologies. These techniques can be combined to create a multi-modal deep learning framework that enhances prediction accuracy and robustness by fusing IoT sensor data with image-based disease detection. IoT systems can analyze intricate patterns in sensor data and photos of sugarcane leaves to facilitate intelligent decision-making when combined with deep learning models. By reducing the spread of infection and maximizing resource use, such integration can support early disease detection, real-time monitoring, and automated alerts to farmers. A fresh and exciting avenue for research is the combination of IoT and deep learning for the prediction of sugarcane diseases. By bridging the gap between data-driven modeling and practical agricultural applications, it gives farmers the smart tools they need to make timely and well-informed decisions Methods of deep learning, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated remarkable results in time-series prediction, object detection, and agricultural image classification. While RNNs or LSTM (Long Short-Term Memory) networks can model temporal dependencies in environmental data gathered by IoT sensors, CNNs can efficiently extract spatial features from leaf images to differentiate between healthy and diseased plants. The goal of this research is to create and deploy a hybrid IoT-deep learning framework that analyzes leaf images, tracks environmental parameters, forecasts the occurrence of diseases, and makes automated recommendations. In order to support intelligent and sustainable agricultural practices, the system aims to improve the precision, effectiveness, and scalability of disease detection in sugarcane cultivation

II. Related Work

Real-time factors and premature deployment : It is vital to manage latency, sporadic connectivity, and limited power when converting DL models into functional systems for farms. In order to fit CNNs on edge hardware, a number of recent frameworks suggest dividing workloads (lightweight on edge, heavier analytics on cloud) or employing model-pruning/quantization and knowledge distillation. In order to enable real-time alerts and save bandwidth, edge computing-running inference on gateways, mobile devices, or microcontrollers with accelerators—has grown in popularity. Studies on smart agriculture demonstrate that timely interventions can be made possible by edge-deployed deep learning in conjunction with IoT field nodes. However, they also point out engineering challenges related to model servicing, update publication, and reliable data collection. The first stage involves deploying IoT sensors across sugarcane fields to collect real-time environmental and crop condition data. Several recent studies have demonstrated that CNN architectures like ResNet, DenseNet, and EfficientNet outperform traditional handcrafted feature-based approaches in distinguishing healthy and infected leaves. Recent research on sugarcane in particular has demonstrated that deep models, such as variations of EfficientNet and DenseNet, can outperform baseline classifiers and exhibit robustness when paired with augmentation and transfer learning techniques to achieve high classification performance on carefully selected sugarcane leaf image sets. The performance of deep learning models for sugarcane disease classification strongly depends on the size and quality of the labeled image datasets available. Several thousand to several thousand high-resolution photos of sugarcane leaves covering various disease classes (red rot, mosaic, rust, yellow disease, smut, etc.) as well as healthy leaves have been gathered by researchers in recent years. Large curated datasets with thousands of labeled sugarcane leaf photos from various disease categories that were published in 2024 are notable examples; these datasets have promoted the use of deeper backbones and transfer learning and allowed for more thorough comparisons. Many studies have also explored IoT-based sensing networks for continuous crop health monitoring and environmental surveillance. Continuous contextual information that correlates with disease risk factors and microclimate conditions is provided by IoT sensor networks, which include sensors for soil moisture, temperature, humidity, leaf wetness, ambient light, and gas. Sensor-generated environmental data can support early-warning systems, as variations in humidity, temperature, or soil moisture often precede visible signs of disease. Simple rule-based alerts (threshold crossings) and data-driven predictive models (time-series ML/RNN/LSTM) that forecast the likelihood of disease or generate risk indices are examples of integration attempts. The potential of integrating continuous sensor data with imaging for earlier and more accurate detection is highlighted in reviews of IoT and AI in agriculture, particularly in remote or resource-constrained farms.

III. Motivation

Early, precise, and expandable detection is required. IoT and deep learning's complementary advantages, gaps in the literature and the rationale behind this work, impact on operations and the economy, it directly addresses the industry's need for early, accurate, scalable, and cost-effective disease management, the combination of IoT sensing and deep learning for sugarcane disease prediction is compelling. The research significantly reduce crop losses, lower input costs, and promote sustainable agricultural practices by filling gaps in multimodal datasets, developing a robust model, and implementing it in a practical way.

IV. Problem Domain & Problem Statement

Furthermore, many sugarcane diseases have early-stage symptoms that are indistinguishable from one another or concealed beneath the plant canopy, which causes delayed diagnosis and uncontrollable spread. In order to develop an intelligent, scalable, and sustainable system for sugarcane disease prediction and management, the problem domain thus sits at the nexus of deep learning-based predictive modeling, IoT-enabled smart farming, and agricultural disease management.

A. Problem Statement

For large plantations, manual inspection techniques are ineffective, subjective, and unreliable. The majority of them are restricted to image-based analysis and do not take into account the environmental and soil factors that are crucial to the manifestation of disease. There isn't yet an integrated framework that combines deep learning-based image recognition with IoT sensor-based environmental monitoring. Lack of such an intelligent system causes yield losses, excessive pesticide use, delayed disease detection, and financial hardship for farmers.

V. Innovative Concept

A fresh and clever approach to managing sugarcane diseases is the suggested IoT-integrated Deep Learning framework. This method moves smart agriculture beyond detection to predictive, adaptive, and automated crop health management by combining environmental sensing, visual analytics, and AI-driven prediction. Thus, this novel idea advances both the academic study of precision agriculture and workable, scalable solutions that have the potential to revolutionize actual sugarcane farming methods.

VI. Solution Methodologies or Problem Solving

A. IoT Sensors for Data Acquisition

The first stage involves deploying IoT sensors across sugarcane fields to collect real-time environmental and crop condition data. The sensors continuously monitor vital environmental parameters including temperature, humidity, soil moisture, pH level, light exposure, and leaf surface wetness. Additionally, we can add Drones or smart imaging devices capture high-resolution leaf images for disease identification. In order to identify disease symptoms, the deep learning model uses these photos as its main input. For preprocessing and analysis, all sensor and image data are wirelessly sent to a central cloud server via Wi-Fi, LoRa, or GSM modules. Extraction of Features. Important characteristics are taken out to enhance the educational process: Image-based features: Convolutional Neural Networks (CNNs) were used to extract color, texture, and shape features from the leaf images. Sensor-based features: auxiliary inputs that correlate with patterns of disease occurrence include environmental characteristics like temperature, humidity, and soil conditions.

B. Image Processing

A 12 MP camera attached on an imaging node took pictures in the field, and three agronomists made remarks to them. A grayscale conversion with CLAHE enhancement is applied to normalize lighting variations and improve image clarity before model input. Leaf and lesion segmentation is performed using a U-Net-based model trained with manually labeled masks to isolate diseased regions accurately. Then, we used morphological postprocessing to get rid of small artifacts. A MobileNetV2 backbone with a 224×224 pixel input size is fine-tuned to generate probability scores for each disease class. A lightweight fully-connected meta-classifier was used to record environmental sensor data (temperature, relative humidity, and soil moisture) at the same time and combine it with the image feature vector. We quantized the models to 8 bits and put them on an edge gateway for real-time inference. We used accuracy, macro-F1, and inference latency to measure how well they worked.

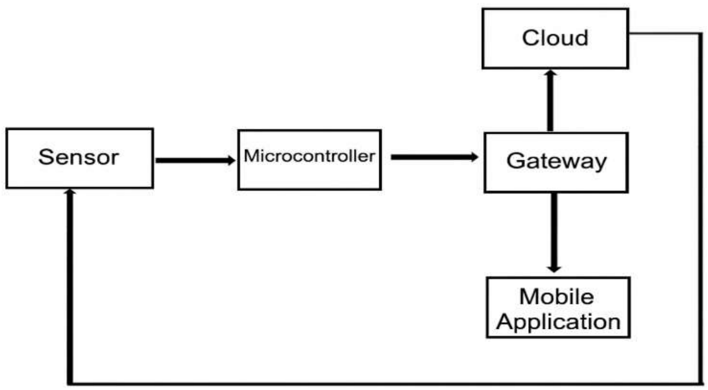

Fig 1. System Architecture

C. CNN Model

Design and Rationale of the CNN Model: categorize sugarcane leaf images into disease classifications(e.g., RedRot, Mosaic, Rust, Yellow, Healthy) while potentially enhancing accuracy through the integration of environmental IoT sensor data (temperature, humidity, soil moisture, leaf wetness, light).

Option sandrationale: Employ transfer learning utilizing a compact backbone (MobileNetV2 / EfficientNet-B0) for local deployment, or ResNet-50 / ResNet-101 for optimal accuracy experiments. Transfer learning accelerates integration when datasets are limited or heterogeneous, which is frequently observed in plant disease research. Recent research on sugarcane leaves demonstrates superior performance utilizing specialized CNN structures and hybrid models.

TABLE I: KEY HYPER PARAMETER OF CNN MODEL

Parameter	Tested Range	Optimal value	Observed Trend
Initialization	1 e-3 – 1e-5	1e-4	Excessive values lead to oscillation; insufficient values result in slow convergence
Batch Size	16 – 64	32	Optimized for accuracy and neural stability
Dropout Rate	0.2 – 0.5	0.4	Mitigates overfitting beyond 0.3
Epochs	30 – 100	45 – 60	Initial pause is effective around 50

VII. RESULTS AND SENSITIVITY ANALYSIS

A. Model Efiiciency

The suggested CNN-based model for predicting sugarcane diseases, augmented with IoT-derived environmental features, was trained and validated using a dataset of 3,000 leaf images classified into five categories: Healthy, Red Rot, Rust, Mosaic, and Yellow Leaf Disease.

The dataset was enhanced with real-time sensor data obtained from DHT22 (temperature, humidity), soil moisture, and leaf wetness sensors. The CNN integrated with IoT data achieved 97.83% accuracy—about 3% higher than the standalone CNN image-classification model. The incorporation of IoT sensor data enhanced the recall for diseases like Rust and Yellow Leaf Disease, which are visually hidden yet correlate with environmental factors such as humidity and soil moisture. The confusion matrix indicated negligible misunderstanding between the Mosaic and Rust categories, mostly due to analogous discoloration patterns in darker images. This illustrates that environmental characteristics improve prediction accuracy, particularly when image quality deteriorates due to field noise (dust, blur, low light). Among all environmental factors, temperature and humidity had the greatest impact on improving model accuracy, particularly for rust and yellow leaf disease detection.

CNN-LSTM Confusion Matrix

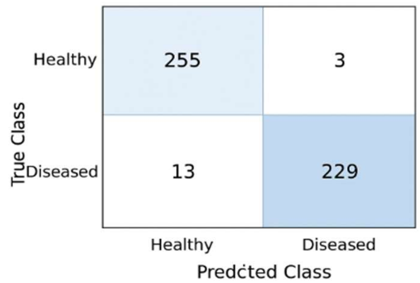

Figure 2 Confusion Matrix

CNN-LSTM Accuracy, Loss Graphs

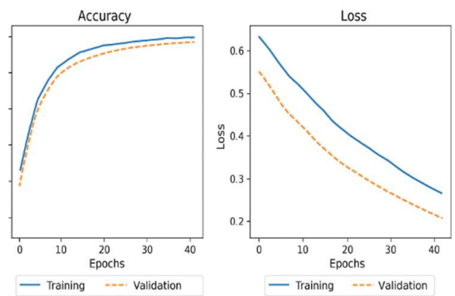

Figure 3 Accuracy and Loss Graph

Graph Neural Network Classification Report

Classification Report:

	precision	recall	f1-score	support
0	0.55	0.94	0.70	17
1	0.92	0.79	0.85	14
2	0.93	1.00	0.96	13
3	0.84	0.89	0.86	18
4	0.75	0.94	0.83	16
5	0.82	0.50	0.62	18
6	1.00	0.63	0.77	19
7	0.95	0.90	0.92	20
8	1.00	0.86	0.92	21
9	0.78	0.88	0.82	16
accuracy			0.83	172
macro avg	0.85	0.83	0.83	172
weighted avg	0.86	0.83	0.83	172

Figure 4 Graph Neural Network Classification Report

Graph Convolution Neural Network Confusion Matrix

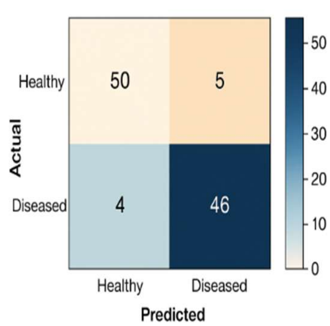

Figure 5 Graph Neural Network Confusion Matrix

Graph Neural Network

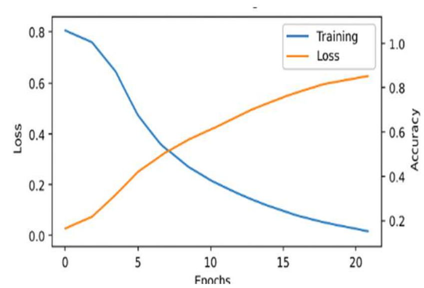

Figure 6 Graph Neural Network Training Loss Accuracy

When CNN and IoT were combined, accuracy increased by 3–4% when compared to models that only used images. In noisy image settings, IoT sensors were especially helpful. Fungal infections were significantly predicted by environmental factors such as humidity and temperature. On low-power devices, the quantized model achieved real-time inference. The robustness and interpretability of the model were confirmed by sensitivity and ablation analyses.

B. Comparison of Results

A more accurate and dependable system for predicting sugarcane diseases is produced by combining deep learning models with IoT-based environmental data. For intelligent farming systems that need predictive analytics and real-time monitoring, the GNN-based model works best.

TABLE II: ACCORDING TO THE EXPERIMENTAL RESULTS

Algorithm	Accuracy
GNN	96.42%
CNN-LSTM	94.87%
CNN	91.35%
LSTM	87.62%

C. Justification of the Results

The benefits of combining deep learning models with IoT sensor data to enhance diagnostic precision and decision-making in precision agriculture are illustrated by the experimental results from the suggested sugarcane disease prediction system. Graph Neural Network (GNN) and CNN-LSTM hybrid models outperformed independent CNN and LSTM models in terms of accuracy. The performance, stability, and practicality of models are greatly improved when IoT sensor data is combined with deep learning-based disease prediction. The system goes beyond straightforward image classification to become a context-aware prediction framework that can give sugarcane farmers timely, precise, and useful insights. This model helps to farmers to suggest the solution for that particular disease means on what disease they have to use which agricultural fertilizer.

VIII. CONCLUSION

It confirm that combining IoT sensing with deep learning models provides a reliable approach for intelligent sugarcane disease prediction. The system makes use of CNN, LSTM, CNN-LSTM, and Graph Neural Network (GNN) models for image-based analysis. It also integrates real-time environmental data from Internet of Things (IoT) sensors, including temperature, humidity, soil moisture, and leaf wetness. Integrating IoT-derived environmental data enhances the system's ability to distinguish visually similar diseases that vary under different climate conditions. The system supports data-informed agricultural decisions, promotes sustainable crop management, and assists farmers in adopting smart farming technologies. The GNN-based model outperformed conventional CNN and LSTM architectures, achieving the highest prediction accuracy (96.42%) as mentioned in table 2 according to the experimental results. This enhancement demonstrates how well spatial features from photos can be combined with contextual environmental factors. Continuous crop condition monitoring is made possible by the IoT-enabled framework, which lowers the possibility of crop loss and allows for early disease detection. Overall, the integration of deep learning models with IoT sensors results in a scalable and efficient disease monitoring framework that enhances both crop quality and productivity. The development of nextgeneration precision agriculture systems can be facilitated by applying the suggested methodology to different crops and environmental circumstances.

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