SAMS: Smart Agricultural Monitoring System Integrating Edge AI and IoT for Early Detection of Rice Crop Stress

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***Abstract*—This paper presents a Smart Agricultural Monitoring System that integrates Edge AI and IoT technologies for early detection of rice crop stress. The proposed system aims to improve agricultural productivity by providing timely insights into crop health. By leveraging Edge AI, the system can analyze data locally on edge devices, reducing latency and bandwidth requirements. IoT devices are deployed in the field to collect data on various parameters such as soil moisture, temperature, and humidity. The collected data is processed using machine learning algorithms to detect signs of crop stress, enabling farmers to take proactive measures to mitigate potential losses. The effectiveness of the system is demonstrated through experimental results and case studies.**

***Index Terms*—Smart agriculture, Edge computing, IoT, Crop stress detection, Machine learning.**

I. Introduction

India, the second largest producer and consumer of rice globally, holds an essential position in the world's rice market. The nation produces more than 100 million tons of rice yearly, which includes the nation's demands and substantially contributes to international markets (FAOSTAT, 2022). An individual consumes about 67 kgs of rice annually, making it a staple diet. Over a lifetime, an individual consumes about 5000 kgs of rice. Rice is not only a staple diet food but also a vital source of energy and nutrition for the human body, serving as a rich source of carbohydrates and providing fuel required for both physical activities and internal functions. In India's rice cultivation context, high humidity, warm temperatures, and waterlogged conditions in rice fields create conducive environments for bacterial and fungal combinations. Pathogens such as Xanthomonas oryzae, Magnaporthe oryzae, and Rhizoctonia solani pose significant threats, causing diseases like bacterial blight, blast, and sheath blight, respectively. Poor drainage, inadequate crop residue management, and stress factors such as drought and nutrient deficits weaken plant defenses, increasing susceptibility to infections. Disease incidence is further intensified by cultural practices such as overcrowding, excessive nitrogen fertilization, and improper irrigation.

In recent years, developments in agricultural technology have enabled innovative crop management and monitoring technologies. One notable approach involves the integration of edge AI (artificial intelligence) and IoT (Internet of Things) in intelligent agricultural monitoring systems. The IoT and edge AI integration offer several benefits compared to traditional monitoring techniques. Firstly, it provides farmers with quick access to actionable knowledge about crop health and environmental conditions, facilitating the early identification of stress, including disease outbreaks, pest infestations, and nutritional deficits. Secondly, these systems ensure real-time decision-making even in remote agricultural settings with limited connectivity by processing data locally at the edge, minimizing dependence on cloud computing resources. Moreover, by automating data collection and processing, farmers can efficiently streamline farm operations, resulting in time and cost savings on labor.

This research paper provides an in-depth study of designing and implementing an innovative smart agriculture monitoring system that seamlessly integrates edge AI and IoT technologies. The goal of this research is to make a significant contribution to improving crop health, maximizing production potential, and increasing sustainability.

Figure 1 shows a Raspberry Pi with a camera module capturing stressed rice crops, using machine learning to send notifications to farmers for field actions.

Fig. 1: Implementing a Smart Agricultural Monitoring System

II. Literature Review

Identifying biotic stress in rice crops has various creative innovations, each proposed with unique suggestions and limitations and exhibiting varying models. Intelligent farming monitoring proposal is based on System flexibility and Edge AI uses an adaptive cryptography engine to make sure that the security of the sensor data[5]. Using a machine learning algorithm, rice blast disease can be identified and detected[10]. Early Identification of Rice Leaf Blast was proposed based on hyperspectral imaging to get an image spectrum of health, mild disease, deficiency of nitrogen, and severe disease. This is used to differentiate rice leaf blast disease from a deficiency of nutrients, an early disease diagnosis[15]. The Proposal of Rice Bios identifies biotic stress in rice crops using deep learning-enabled handheld devices based on Artificial intelligence, which uses portable computing power[7]. The proposed Optimized Light-Weight Deep Learning Model for Rice Disease Identification was used to improve the CNN model for deployment on edge devices to identify rice leaves[12]. The RiceCloud proposal uses deep learning techniques to feed the image into the well-known transfer learning neural network; VGG 16 uses an image dataset that has been pre-trained[1].

The proposal of Understanding the responses of Rice to environmental stress using proteomics uses methods for investigating proteomics and responses to different stress situations[13]. The proposal of applying thermal imaging and hyperspectral remote sensing for crop water deficient stress monitoring determines various genotypes that respond to water deficiency stress[8]. The proposal of Rice crop monitoring with unmanned helicopter remote sensing images uses Precision Agriculture which is a cutting-edge technique that preserves the productivity of crops and reduces crop damage[14].

The proposal of Salinity Stress Detection in rice crops using time series MODIS VI data examines the behavior of rice crop phenological indicators under different salinity levels as well as the temporal trend of salinity in the kharif season [9]. The proposal of the role of microorganisms in the adaptation of crops to abiotic stresses is used to create short-term, low-cost biological solutions for managing abiotic stress [4]. Microbial proposal talks about contributions for rice production from conventional crop management to the use of "omices" technologies[3].

Microbes play a crucial role in supporting sustainable rice production using the system of rice intensification. By using SRI methods, farmers enhance the development of rice plants, yield, and resilience. [2]. The proposal of an AI-based hybrid CNN: LSTM model for crop disease addresses pest prediction and variation for rice plant yellow stem border(YSB) disease [6]. The Paddy Crop Disease prediction proposal uses a deep learning algorithm that has significantly increased agriculture productivity and output[11].

TABLE I: Comparison with Existing Models

Related Works	**Work flow**	**Edge AI**	**Internet**	**Comp. Power**	**H/w accel-erators**
Kaur et al. [5]	Yes	No	Required	High	Required
Goel et al. [6]	No	No	Required	Moderate	Required
Hasan et al. [10]	No	No	Required	High	Required
Yang et al. [11]	Yes	No	Required	Low	Not Re-quired
Kim et al. [12]	No	No	Required	Moderate	Required
RiceBios	Yes	Yes	Not Re-quired	Moderate	Not Re-quired

The above Table I represents a comparative analysis of existing models. Each column indicates vital aspects such as workflow, edge AI, internet, computational power, and Hardware accelerators.

A. Research Gap

The solutions mentioned above have each helped monitor biotic stresses in rice crops and predict diseases uniquely. They have done this by suggesting accurate classification models, analyzing images, or combining sensed data and images to make decisions. This study introduces an innovative method for detecting rice crop health using a real-time system with Raspberry Pi camera modules. In contrast to other methods, this system prioritizes timely and visual notifications, allowing farmers to identify potential issues.

III. SAMS: The Proposed Model

The proposed system, the Smart Agricultural Monitoring System (SAMS), uses the Raspberry Pi camera module to improve rice crop health monitoring accuracy and efficiency. There are some critical steps in this implementation process for the system to work flawlessly:

1) **Raspberry Pi camera module:** First, set up the Raspberry Pi camera module in the rice fields to monitor them. The camera modules are placed so that they can capture images of the crop at a particular interval to provide a real-time study of the rice harvest. The system can adequately identify different conditions, such as healthy, fungal, and bacterial leaves.
2) **Edge AI:** Generate the Edge AI, which plays a crucial role in the Smart Agricultural Monitoring System by making it highly efficient.
3) **Machine Learning Model:** A pre-trained machine learning model is employed. This model has learned patterns from a large healthy and stressed rice crop dataset.

4) **Feature Extraction:** The model extracts relevant features from the image, such as color variations, texture, and leaf shape.
5) **Classification:** Based on these features, the model classifies the crop as healthy or stressed.
6) **SAMS Training Model:** The model's accuracy is crucial. To improve it, the system uses training data for SAMS. SAMS data includes labeled examples of stressed and healthy rice crops. The training process adjusts the model's internal parameters to distinguish between healthy and stressed conditions better.
7) **Stress Identification:** Once the model is trained, it's ready for real-world use. When a new image is captured, the model evaluates it. If the features match those of stressed crops, the model flags it as stressed. Otherwise, it classifies the crop as healthy.
8) **Message to Farmer:** The system communicates with the farmer through a mobile app integration. If stress is detected, the farmer receives a message that informs them about the crop's status.
9) **Action:** Armed with real-time insights, the farmer takes action. If the crop is stressed, they follow the recommended steps. If the crop is healthy, they continue regular practices, and the timely response helps maintain crop health and productivity.

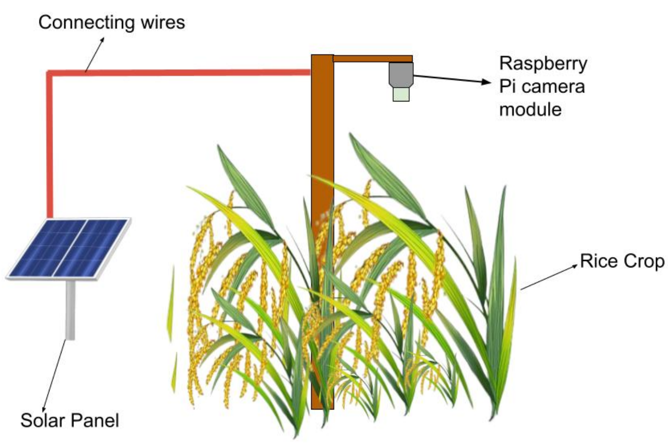

Fig. 2: SAMS Solution using Edge AI

Figure. 2 depicts a SAMS Solution using Edge AI for monitoring rice crops. It uses a Raspberry Pi camera module that is linked to a solar panel to capture pictures of rice crops. The system aims to enhance crop management and yield prediction.

A. Image Dataset

TABLE II: Dataset Table

STATE	CATEGORY	IMAGES	SIZE
Healthy	-	20	11.5MB
Biotic stressed	Bacterial	40	16.9MB
Biotic stressed	Fungal	34	10.6MB

Above Table II represents the dataset of the images of the rice leaves, which are divided into three categories: Healthy, Biotic Stressed-Fungal, and Bacterial.

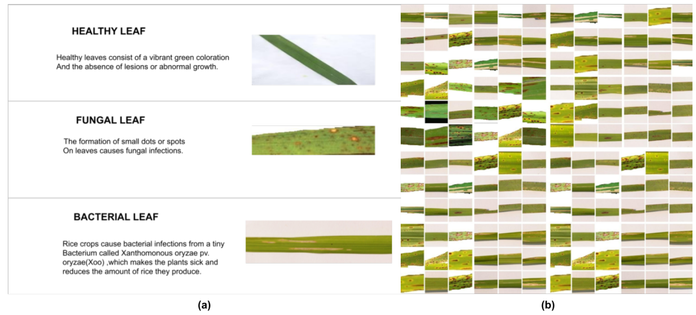

Fig. 3: Categories of Leaf

B. Algorithm for Crop Health Notification to Farmer's Mobile App (Edge AI Only)

1) Initialize SAMS
   a) Set up Hardware Components
   b) Capture image()
      i) CapturedImage = captureImageUsingCameraModule()
2) Define the schedule for taking photos
   a) Let 'd' be the set of all crop images taken over time 't'
   b) s be a schedule function that determines the times at which the Raspberry Pi camera module takes a photo
   c) Capture Image d at time t such that $d = s(t)$
3) Analyze Image using Machine Learning Algorithm
   a) CropHealth = AnalyzeImage(CapturedImage)
   b) $f : D \rightarrow \{0, 1\}$ be a function where
      i) $f(d) = 1$ if crop image d shows signs of stress, and
      ii) $f(d) = 0$ otherwise.
   c) return CropHealth
4) Generate Notification Message(cropHealth):
   a) M is the message function that constructs the message to the farmer based on the analysis, $M : \{0, 1\} \rightarrow Messages$
   b) Construct message $m = M(1)$
   c) If $f(c) = 1$ (stress detected):
      i) cropHealth = "stressed"
      ii) return "Your crops require attention. They are currently stressed."
   d) Else
      i) return "Great news! Your crops are healthy and thriving."
   e) Wait until the next scheduled time t' where $t' > t$.
5) Mobile App Integration():
   a) Setting up communication protocols

b) Farmer's mobile app listens for notifications timely.

6) Receive And Display Notification():
   a) Farmer's mobile app displays received notifications to the user
   b) A be the action function executed by the farmer in response to the message received.

C. Analyzing the Image

The system immediately analyzes pictures taken by the Raspberry Pi camera module without relying on remote or cloud computing. Edge AI categorizes visual details in the leaf into three types: Healthy leaf, fungal leaf, and bacterial leaf. The Raspberry Pi captures crop images at scheduled intervals, running a script or program for this process. **Machine Learning Analysis:** A pre-trained machine learning model on the Raspberry Pi determines the crop's health status after capturing images, identifying whether it is "healthy," "fungal," or "bacterial." **Notification Generation:** Based on the machine learning model outcomes, the Raspberry Pi generates a notification. For instance, a "healthy" crop triggers a notification in the "green box," a "fungal" crop in the "orange box," and a "bacterial" crop in the "red box." Notifications are sent directly to the farmer's mobile through SMS or push notification on their mobile app.

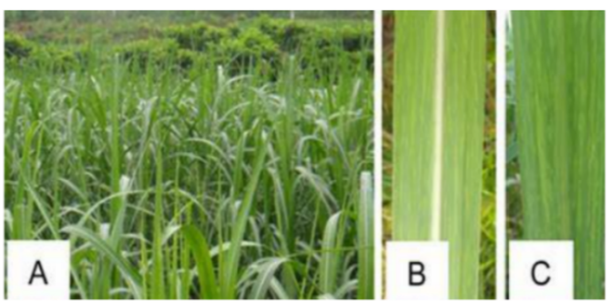

Fig. 4: Sample clicks by Raspberry Pi camera module

In the above Figure. 4, [A] is a click of a rice field from a normal camera, and [B] and [C] are the clicks of a healthy rice crop clicked by the Raspberry Pi camera module.

This study uses a supervised machine learning technique to identify the bacteria on the rice crop. Data collection, preparation, identification of features, model training, and evaluation were among the crucial processes in the methodology. Quality images of all three kinds of leaves, Bacterial, Fungal, and Healthy rice leaf images are collected from different regions to ensure the machine's durability. Data pre-processing methods such as image organization, resizing, and augmentation are applied to enhance the quality and diversity of the dataset images.

The green plant leaf is the focal point. It exhibits brown spots, which could be indicative of various issues: The left graph (Fig. 6) (a) displays an image of a green leaf with multiple dark-colored, presumably brown, spots. These spots could indicate issues affecting the leaf's health. The x and y-axes are numbered from 0 to 400, providing a scale for measurement. The leaf's appearance suggests it may suffer from a disease or environmental stress. The right graph (Fig. 6) (b) represents a processed version or analysis result of the left graph's image. Machine learning techniques have been applied to interpret the data. The blue lines and dots likely correspond to the distribution and intensity of brown spots on the leaf. The machine learning model can identify potential issues and classify the leaf's condition by analyzing these patterns.

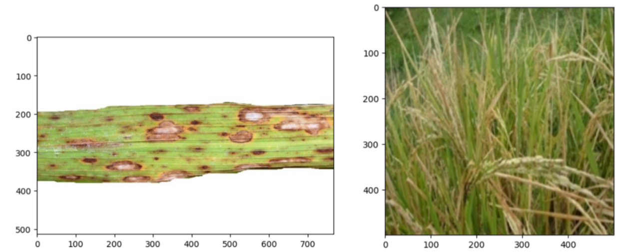

Fig. 5: Green leaf with brown spots

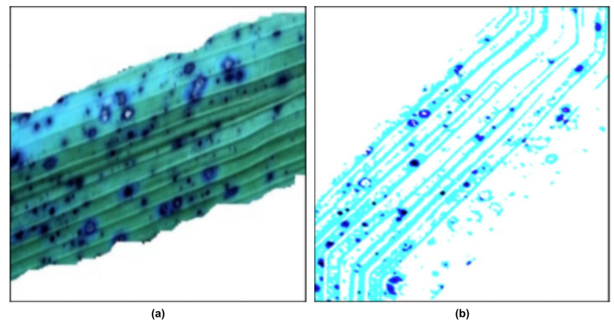

Fig. 6: Analysis of leaf condition

IV. Results and Discussion

A. Performance Analysis

The above image contains four sections featuring line graphs tracking "Loss" and "Accuracy" during the training of a machine learning model, along with images labeled "Predicted" showing model outputs. **Loss Graph:** The loss graph tracks the training and validation loss over 100 iterations. The training loss starts high but decreases steadily, whereas the validation loss shows more fluctuation, indicating potential overflow. **Accuracy Graph:** The accuracy graph illustrates training and validation accuracy over the same iterations. The accuracy during training is always higher than the accuracy during validation. **Predicted Images:** A blurry image representing model prediction is on the left, contrasting with the clear image on the right.

B. Mobile App Integration

The app below made using machine learning prediction, is user-friendly. The farmer needs to enter the ID Number assigned and then can see the plant image, whether it is healthy or stressed. After analyzing the image, it generates a notification to the farmer in two different ways as shown

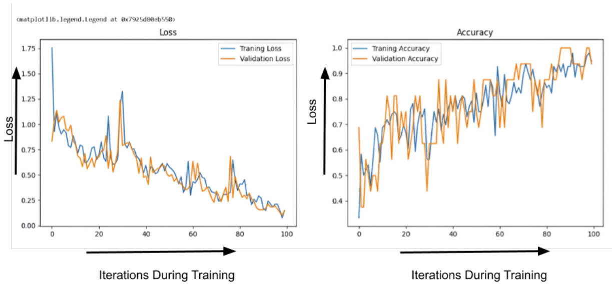

Fig. 7: Loss and Accuracy Graph

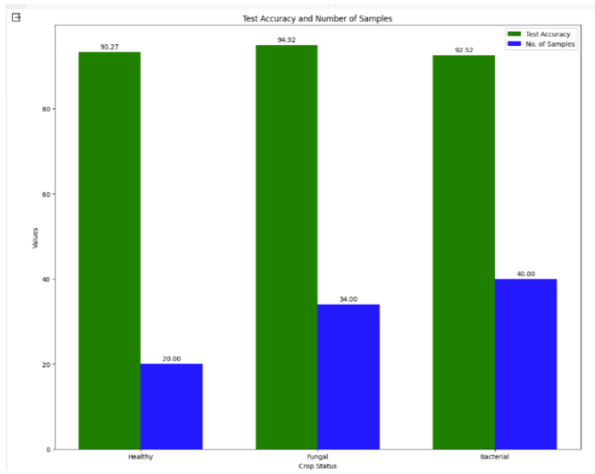

Fig. 8: Graph representing Test Accuracy and Number of Samples

below: if the crop is healthy, then the farmer receives a notification in green color indicating that the crop is safe, and if the crop is affected by the bacteria, then the farmer is notified with red color indicating that the crop is not safe. This helps farmers respond quickly to information through a clear presentation.

Fig. 9: Mobile App Integration and Notification

Fig. 9 (a), Fig. 9 (b), Fig. 9 (c), Fig. 9 (d), Fig. 9 (e) describes the mobile app integration and notification generation to the farmers about their crop condition.

Conclusion

This study outlines an innovative agricultural monitoring system using Edge AI and IoT to detect crop stress early by capturing images without cloud computing. It enables farmers to make real-time decisions, identify subtle signs of stress, and allow timely interventions. The outcomes demonstrate its effectiveness in providing timely information for proactive crop management, which is crucial for food security and precision agriculture.

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