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Innovative Solutions for Agriculture: Sensor-Driven Soil Parameter Monitoring and Deep Learning in Potato Disease Detection

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Abstract— The primary obstacle facing modern agriculture is the lack of advanced technologies capable of efficiently and proactively identifying crop diseases, a gap that is most noticeable while the crop is at the key stem stage. Taking note of this difficulty, the suggested solution calls for the deliberate insertion of cutting-edge sensors at the root level straight into the soil. The objective of this integration is to offer a comprehensive and in-depth evaluation of crucial factors that are necessary for plant health, including temperature dynamics, moisture content, and nutrient levels of soil. While the temperature sensors serve a dual purpose by monitoring the external environment and evaluating the condition of mechanical assets vital to agricultural operations, the soil moisture and index sensors are essential for precisely determining irrigation needs and assessing soil nutrient levels. The project incorporates a cutting-edge Convolutional Neural Network (CNN) deep learning algorithm designed especially for the identification of potato leaf diseases, which represents a significant improvement to disease detection capabilities. This sophisticated algorithm improves the accuracy and efficiency of disease identification by using deep learning to analyze and comprehend complex patterns found in the leaf of the plant. This comprehensive initiative's main goal is to create a seamlessly integrated sensor system that can monitor crop health dynamically, provide real-time insights into critical soil characteristics, and use state-of-the-art CNN deep learning technology to detect potato leaf diseases in the agricultural landscape with extreme precision.

Keywords— Early Detection, Sensor Integration, CNN Deep Learning Algorithm, Potato Leaf Disease, Agricultural Technology, Convolutional Neural Network.

I. INTRODUCTION

A crucial component of the world's food supply and the sustenance of human life is agriculture. But this business has a lot of obstacles to overcome, the most important of which is the constant threat posed by crop diseases. These diseases, which can be caused by viruses or fungus, present a serious threat to crop quality, productivity, and international food supply chains. To tackle this issue, it is necessary to include cutting-edge technologies, such as deep learning algorithms and sensor systems, to detect crop illnesses early and take preventative measures.

This journal describes a novel advancement in agricultural technology—the creation of an algorithm for Convolutional Neural Networks (CNNs) intended especially for the detection of potato diseases. When an uploaded image of a potato leaf is given to the algorithm, it shows impressive accuracy in differentiating between healthy and diseased leaves. In order to evaluate important factors like temperature, soil moisture, and nutrient levels, the study incorporates soil sensors. Farmers can then assess whether the current conditions are within the ideal range in real time by looking at these parameters, which are then prominently displayed on an LCD screen. This creative fusion of sensor technology and deep learning holds great potential for improving precision agriculture and providing farmers with timely information that is essential for crop health management

1.1 PROBLEM STATEMENT:

In this rapidly changing world, agriculture is facing lot of backlash due to disease causing pests, due to this yield is reducing. To tackle this issue a soil parameters like temperature, moisture and most importantly nutrient values like nitrogen, phosphorous, potassium values are monitored using Arduino sensors and along with this created a Deep learning model to disease detection in potato leaves.

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1.2 SCOPE:

This project is for real time soil parameters monitoring and using Deep learning CNN algorithm detection of disease in potato leaves and can be extended to other crops for leaf disease detection.

1.3 OBJECTIVES:

The main objectives of this work are:

- To protect crops from insects and pests
- To integrate Deep learning algorithm and sensors.
- Disease detection using deep learning algorithm.

This project combines deep learning algorithms with sensor technologies to protect crops from pests using creative methods. The use of sophisticated image analysis for the early detection of crop diseases is also emphasized. The primary objective is to improve precision farming, maximize resource efficiency, and support sustainable agriculture through the application of state-of-the-art technologies for effective crop protection and disease control.

1.4 ORGANIZATION

The structure of this paper is as follows: The first part ofSection 2 describes the literature review of agriculture monitoring and disease detection. The proposed approach and architecture are then detailed in the following Section 3, which follows. Section 4's conclusions and outcomes are discussed there.

II.RELATED WORKS

The research explores diverse imaging techniques, including thermal, hyperspectral, multispectral, and 3D imaging, for disease detection. Additional methodologies such as Support Vector Machines (SVM), K-Means clustering, K-NN, and deep learning are employed for early determination of diseases. The findings underscore the necessity for more efficient methods with cost-effectiveness in mind. Notably, hyperspectral and multispectral imaging techniques demonstrated an 89% accuracy in disease detection. However, identified gaps in the research highlight the continued challenges and costs associated with early-stage disease detection, particularly the absence of automatic cluster center initialization. The study underscores the need for automated plant leaf disease detection algorithms to enhance efficiency and addresses ongoing requirements for advancements in the field [1].

The research focuses [2] on the development of a mobile client-server model specifically designed for disease detection in plants. Utilizing the CIE lab (International Commission on Illumination) color-based unsupervised leaf disease segmentation, the study proposes optimized image processing algorithms to effectively segment and detect leaf diseases using mobile devices. The mobile application successfully identifies diseases such as leaf spots and leaf blight, achieving an impressive accuracy of 93%. However, challenges persist in accurately identifying diseases when a leaf is captured against a complex background, and issues arise when capturing shadows or reflections, potentially leading to color variations in the digital representation of the leaf due to changing seasons. These identified gaps emphasize the need for further research to address the intricacies associated with capturing and analyzing leaves in real-world conditions.

In Bagheri's research [3], aerial Multispectral imagery was applied via UAV for the detection of fire blight infestation on four-week-old watermelon transplants. Leaves were collected and tested, and spectral data were chosen using a benchtop hyperspectral imaging system. The findings indicated high specificity and sensitivity for disease detection, achieving an accuracy of 89%. However, gaps in the study were identified, including the absence of spectral data collection when disease severity exceeded 75%, attributed to the poor condition and desiccation of the leaves. Additionally, the research highlighted a lack of successful UAV-based systems for the detection of disease severity, emphasizing the need for further developments in this area.

The utilization of digital image processing and computer vision in plant diagnosis for disease identification has proven highly beneficial, as digital images are considered reliable for this purpose. However, identified gaps in the existing work highlight challenges in accurately segmenting regions of interest due to complex backgrounds containing elements that can impede proper segmentation. Moreover, the difficulty in controlling capture conditions can lead to unpredictable variations in image characteristics, posing challenges for disease identification. Another significant challenge is the lack of defined boundaries for most symptoms, as they often gradually fade into normal tissue, complicating the clear delineation between healthy and diseased regions. Addressing these challenges is crucial for advancing the precision and effectiveness of plant disease identification using digital image processing [5].

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2.1 SOFTWARE REQUIREMENTS The basic software requirements include**:**

- Arduino IDE, is installed on the system.
- Machine Learning and Artificial Intelligence library like TensorFlow

2.2 HARDWARE REQUIREMENTS

The working platform requirements are

- Arduino UNO board
- Temperature, Moisture, NPK sensors
- LCD for Display of Values.

III METHODS

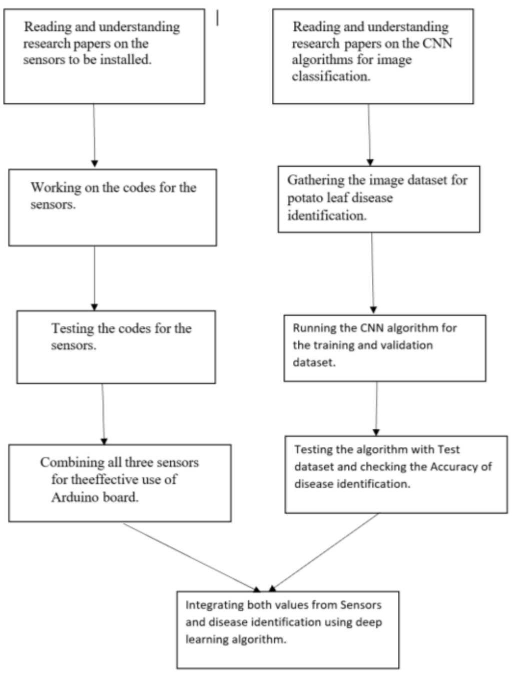

Figure 1 Workflow of the project

3.1 REAL TIME SOIL PARAMETERS MONITORING:

In this study, real-time data collection and monitoring in agricultural settings were made possible by the use of Arduino Sensors to build strong connections with temperature, soil moisture, and NPK sensors. These sensors were integrated seamlessly thanks to the complex network of Arduino connections, which made it possible to precisely measure and retrieve vital parameters that are vital to plant health. An LCD screen effectively displayed the collected data, which included temperature readings, soil moisture content, and NPK values. This gave farmers a user-friendly interface for keeping an eye on the crop's environmental conditions. In addition to demonstrating a novel approach to sensor integration, this Arduino-based system offers a workable and approachable way to improve precision agriculture techniques and encourage well-informed decision-making for the best crop management.

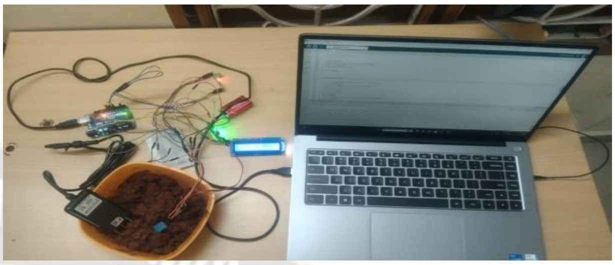

Figure 2 NPK, Temperature, Moisture sensor connections with Arduino and LCD

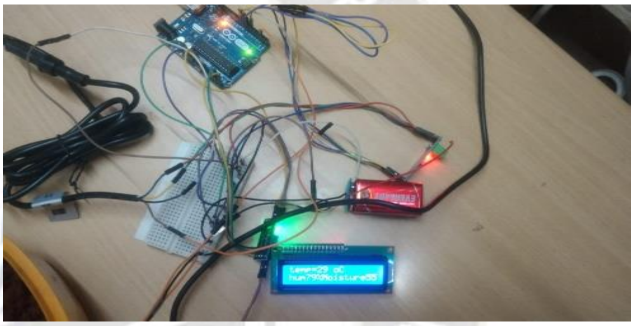

Figure 3 LCD displaying temperature, humidity, Soil Moisture.

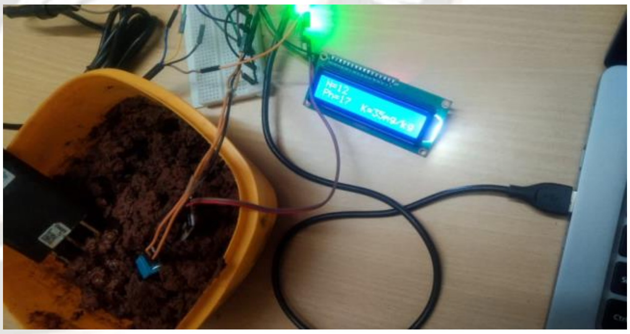

Figure 4 LCD displaying Nitrogen,

Phosphorous, Potassium values in mg/kg

DEEP LEARNING ALGORITHM FOR POTATO LEAF DISEASE DETECTION

Potato (Solanum tuberosum) is one of the world's most important staple crops, providing sustenance to millions of people. However, potato cultivation is constantly threatened by variousdiseases, and among the most destructive are late blight

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(Phytophthora infestans) and early blight (Alternaria solani). These two diseases have the potential to cause significant damage to potato crops, leading to substantial economic losses and food security concerns. Therefore, the timely and accurate detection of late blight and early blight in potato leaves is of paramount importance in agriculture.

Late Blight (Phytophthora infestans): Late blight is a highly contagious and devastating potato disease caused by the oomycete pathogen Phytophthora infestans. This disease is notorious for its ability to spread rapidly under favorable environmental conditions, leading to severe defoliation and yield loss. Late blight primarily affects the leaves, stems, and tubers of the potato plant, resulting in characteristic brown lesions, leaf curling, and eventual plant death. The economic impact of late blight is enormous, as it necessitates frequent and often expensive fungicide applications to mitigate the damage.

Figure 5 Late blight infected leaf

Early Blight, caused by the fungus Alternaria solani: It is a significant threat to potato cultivation, resulting in dark concentric rings with necrotic lesions on the leaves, primarily affecting foliage and causing reduced photosynthesis, premature leaf drop, and decreased tuber yield. While it may not be as aggressive as late blight, it still inflicts considerable economic losses and often requires fungicide use. Given the substantial impact of late blight and early blight on potato crops, there is an increasing need for advanced detection methods, as traditional manual scouting is time-consuming and labor-intensive, making early detection challenging. Advanced technologies such as deep learning Convolutional Neural Networks (CNN) have become crucial for automating disease detection by analyzing images of potato leaves, providing accurate, rapid, and non-destructive disease diagnosis, thus improving disease management and reducing the need for fungicides.

Figure 6 Early blight infected leaf

3.1.1 DATASET COLLECTION AND MODELLING

A dataset containing 2,152 images was obtained from Kaggle and used to train a plant disease classification model. Of these, one thousand photos showed late blight, one thousand more showed early blight, and fifty-two showed healthy plants. Ten percent of the images were assigned to the test and validation datasets in order to evaluate the performance of the models, and the remaining 80% of the images were used for model training. The purpose of this dataset is to aid in the creation and assessment of machine learning models that reliably detect and categorize plant diseases, with an emphasis on late blight, early blight, and healthy conditions.

Model Architecture: The CNN model is created using the Sequential API, which allows you to stack layers sequentially. The architecture includes a series of convolutional (Conv2D) and max- pooling (MaxPooling2D) layers (Figure 7). Convolutional layers extract features from the input images, whilemax-pooling layers reduce spatial dimensions. The model starts with a Conv2D layer with 32 filtersand a ReLU activation function. After each convolutional layer, a MaxPooling2D layer follows with a (2,2) pool size to down sample the feature maps. The model concludes with a fully connected neural network section, consisting of a few dense layers. The final dense layer has the number of neurons equal to n_classes with a softmax activation function, enabling multi-class classification.

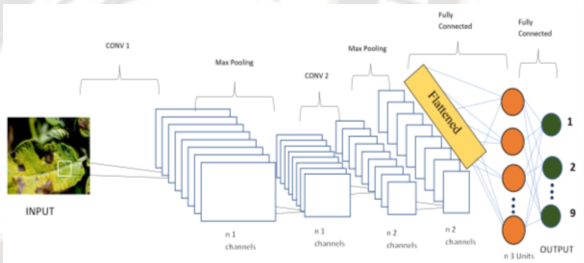

Figure 7 Model Architecture

Model Compilation: The model is compiled using the Adam optimizer, a common choice for gradient-based optimization. The loss function measures the dissimilarity between predicted and actual class labels. The model's performance is evaluated using accuracy as a metric.

Model Training: The model fit method is used to train the CNN model. It takes the training dataset (train_ds), the number of epochs (EPOCS=25), batch size (BATCH_SIZE=32), and the validation dataset (val_ds). During training, the model learns to classify potato leaf images into one of the defined

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classes based on the features it extracts from the images.

Model deployment:

The created model is deployed using FastAPI web application for deploying a machine learningmodel for potato leaf disease detection locally. It has one endpoint:

/predict: This endpoint is designed to receive image files for inference. When an image is uploaded, the FastAPI application uses TensorFlow to load a pre-trained machine learning model (located at "../models/1") designed for potato leaf disease classification. The uploaded image is processed, and the model predicts the disease class among "Early Blight," "Late Blight," or "Healthy." The result is then returned, including the predicted class and the confidence level of the prediction. The application runs on the local host, allowing users to send images for disease classification through a user-friendly interface. This setup makes it convenient to apply the model for real-time predictions on locally hosted web pages, offering a practical tool for agriculture orplant disease monitoring**.**

IV. RESULTS AND DISCUSSION

Using a Convolutional Neural Network (CNN) deep learning architecture, a set of nine images from the test dataset were tested during the model validation phase. Figure 8 provides a concise illustration of the results of these evaluations by showing the predicted class and accuracy score for each image. With the use of deep learning techniques, this representation offers a thorough overview of the model's performance on the validation set and demonstrates its ability to accurately classify a variety of images. CNN is used to improve the model's ability to recognize complex patterns and features in the images, which strengthens the model's performance in image classification tasks.

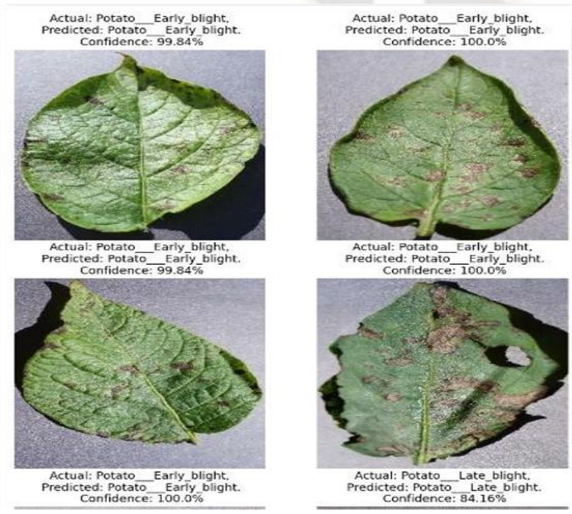

Figure 8 Detecting leaf diseases with accuracy

After validation, Figure 9 presents a detailed analysis of the learning dynamics of the model, showing training versus validation accuracy and training versus validation loss over training epochs. These graphs are useful visualizations that provide information about the model's performance on the training and validation datasets as well as its generalization abilities. The model's ability to perform on unseen validation data is highlighted by the training versus validation accuracy graph, which shows how well the model is learning from the training data without overfitting or underfitting. Simultaneously, the training versus validation loss graph shows how the model is optimized, showing how loss is decreased during training while maintaining consistent performance on validation data.

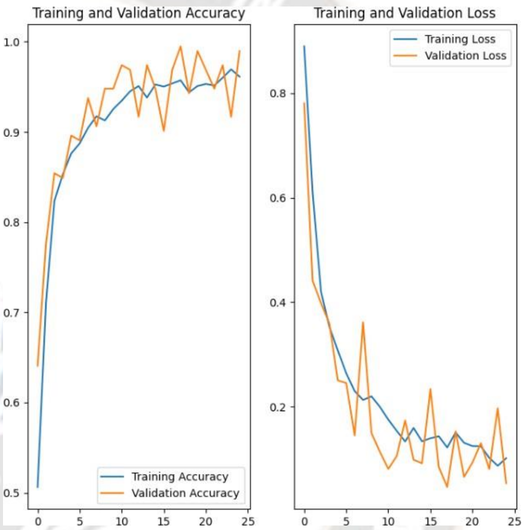

Figure 9 Training v/s validation Accuracy and Training v/s Validation Loss graphs

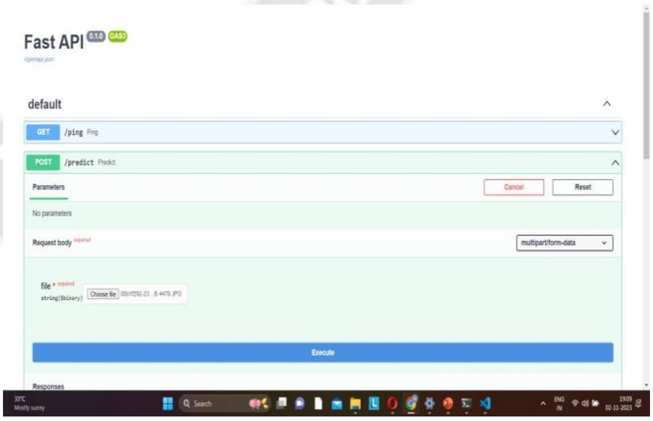

Figure 10 Local host interface where late blight diseased image is selected

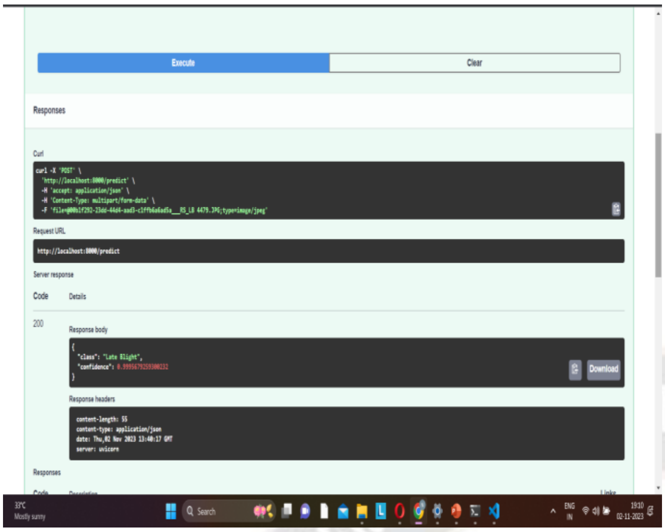

Figure 11 It detects the late blight disease with 99.9% accuracy

Tested the predictive power of a plant disease classification model by deploying it on a FastAPI (Fast Asynchronous Application Programming Interface) local host server. A late blight image was used as the test image (Figure 10), and the model accurately predicted the condition with a 99.9% confidence level (Figure 11). This result highlights the model's ability to recognize late blight in plant photos, highlighting its potential for practical uses in agriculture and plant health monitoring. The FastAPI server made the inference process easy and efficient, showcasing the usefulness of using machine learning models locally to diagnose diseases.

V CONCLUSION

In conclusion, with a 96% accuracy rate, our research represents a noteworthy advancement in the identification of potato diseases. This extraordinary precision was made possible in large part by the application of a Convolutional Neural Network (CNN) algorithm, which also proved to be effective in identifying minute details linked to a range of diseases that impact potato crops. The capacity of CNN to discern intricate patterns in images has been crucial in furnishing a dependable and precise diagnosis, consequently augmenting early detection capacities.

Our approach has been made more comprehensive by adding sensors that measure critical environmental parameters like temperature, soil moisture, and Nitrogen, Phosphorous, Potassium (NPK) values, in addition to disease identification. Farmers are given immediate access to actionable insights into the environmental conditions of their crop thanks to the real-time display of these crucial metrics on an LCD screen. Our approach is positioned as a comprehensive precision agriculture solution because it simultaneously prioritizes accurate disease identification and real-time environmental monitoring. In addition to facilitating the prompt application of focused disease control tactics, it guarantees the best possible crop health and yield. Our research highlights the importance of integrating cutting-edge technologies to bring in a new era of data-driven decision-making in sustainable and effective potato cultivation practices as we navigate the complexities of modern agriculture.

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