"IOT-INTEGRATED MACHINE LEARNING MODEL FOR SMART CROP YIELD PREDICTION"

Reeba Rani[1], Satish[2], Vikram[3]

[1]*Computer Science and Engineering Department, Guru Nanak Dev Engineering College Bidar, Karnataka, India*
[2]*Computer Science and Engineering Department, Guru Nanak Dev Engineering College Bidar, Karnataka, India*
[3]*Computer Science and Engineering Department, Guru Nanak Dev Engineering College Bidar, Karnataka, India*

[1]**reebarani23@gmail.com**
[2]**sonupawar2006@gmail.com**
[3] **mankarivikram0@gmail.com**

Abstract

Agriculture plays a vital role in sustaining the global economy, yet crop yield prediction remains a challenging task due to the influence of multiple dynamic factors such as soil quality, weather conditions, irrigation, and pest infestations. Traditional methods of yield estimation are often inaccurate, time-consuming, and fail to adapt to real-time changes. To address these limitations, this project proposes an IoT-integrated Machine Learning model for Smart Crop Yield Prediction. The system leverages IoT sensors to collect real-time agricultural data including soil moisture, temperature, humidity, rainfall, and nutrient levels. This data is preprocessed and fed into machine learning algorithms to predict crop yield with higher accuracy. The integration of IoT ensures continuous monitoring and data acquisition, while machine learning provides predictive insights by analyzing historical and real-time datasets. The proposed model is designed to assist farmers and agricultural stakeholders in making informed decisions regarding crop selection, resource allocation, and risk management. By comparing evaluation metrics such as accuracy, precision, and recall across different algorithms, the system identifies the most efficient predictive model. The results demonstrate that IoT-enabled machine learning significantly improves prediction reliability compared to conventional approaches. This project contributes to the advancement of smart agriculture by combining IoT technology with data-driven machine learning techniques, thereby promoting sustainable farming practices, optimizing resource usage, and enhancing productivity. The developed system can be scaled for diverse crops and regions, offering a practical solution to modern agricultural challenges.

Keywords- IoT, Machine Learning, Crop Yield Prediction, Deep Learning, MobileNetV2, TensorFlow Lite, Smart Agriculture.

1. Introduction

Agriculture is the backbone of food security and economic stability across the globe, particularly in developing countries where a major portion of the population depends on farming for livelihood. However, crop production is constantly challenged by various plant diseases caused by fungi, bacteria, viruses, and environmental factors. These diseases severely affect crop yield, reduce quality, increase production costs, and in extreme cases lead to complete crop failure. Timely detection of plant diseases is crucial for effective treatment, prevention of disease spread, and ensuring agricultural sustainability. Traditional methods of plant disease detection rely on manual inspection by agricultural experts. This process is time-consuming, labor-intensive, and often not accessible to farmers in remote rural areas. Additionally, symptoms of many diseases closely resemble each other, making manual diagnosis prone to errors. With rapid advancements in Artificial Intelligence (AI), particularly in deep learning and computer vision, automated disease detection through images has become a viable and accurate solution. Among the various AI techniques, Convolutional Neural Networks (CNNs) have demonstrated superior performance in image classification tasks. They can learn disease-specific patterns from leaf images and classify them with high accuracy. However, deploying large deep learning models on mobile devices is challenging due to limited computational power, storage, and memory. Therefore, lightweight architectures such as MobileNetV2, combined with TensorFlow Lite (TFLite), enable real-time offline inference on smartphones. This project focuses on developing an offline crop disease detection mobile application that uses a TFLite-optimized deep learning model integrated into a React Native mobile app. The application allows farmers to capture a leaf image, classify disease types instantly, and receive confidence scores—all without requiring internet connectivity. The solution is cost-effective, fast, and suitable for rural agricultural environments where internet access is limited or unavailable. The following sections detail the background of the study, existing research, motivation behind the work, problem definition, objectives, and the overall structure of this thesis.

2. Related Work

Previous research in smart agriculture has focused on applying machine learning and deep learning techniques for crop yield prediction and plant disease detection. Studies such as those by Mohanty et al. demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in identifying plant diseases with high accuracy using large datasets like PlantVillage. Similarly, Brahimi et al. and Too et al. explored advanced deep learning models such as VGG, ResNet, and DenseNet, achieving improved classification performance through transfer learning.

In addition to image-based analysis, several researchers have used machine learning algorithms like Random Forest, Support Vector Machines (SVM), and Decision Trees for predicting crop yield based on environmental factors such as soil quality, temperature, and rainfall. Some works also integrated IoT sensors to collect real-time agricultural data, enabling more accurate and dynamic predictions.

However, most of these existing systems rely heavily on cloud-based infrastructure, requiring continuous internet connectivity for data processing and model inference. This creates challenges in rural and remote areas where network access is limited or unreliable. Moreover, many deep learning models used are computationally heavy and not optimized for mobile or edge devices.

Therefore, there is a clear need for a lightweight, efficient, and offline-capable solution that can run directly on mobile devices. This project addresses these limitations by combining IoT-based data collection with a MobileNetV2 deep learning model optimized using TensorFlow Lite, enabling fast, accurate, and offline predictions suitable for real-world agricultural applications.

3. Materials and Methods

The proposed system integrates IoT technology and machine learning techniques to enable smart crop yield prediction and disease detection. IoT sensors are utilized to collect real-time agricultural data, including soil moisture, temperature, humidity, rainfall, and nutrient levels. This data is continuously monitored and transmitted for further processing.

A labeled dataset consisting of crop leaf images from multiple categories such as rice, guava, and jowar is used for disease detection. The collected data undergoes preprocessing steps such as image resizing to 224×224 pixels, normalization, and data augmentation techniques including rotation, flipping, and zooming to improve model performance and generalization.

For model development, a deep learning architecture, MobileNetV2, is employed due to its lightweight and high efficiency for mobile-based applications. Additionally, machine learning algorithms are used for analyzing environmental data to predict crop yield. The trained model is then converted into TensorFlow Lite (TFLite) format to enable fast and offline inference on mobile devices.

A mobile application is developed using React Native to integrate the trained model. The application allows users to capture leaf images or input data and obtain real-time predictions along with confidence scores. This approach ensures a cost-effective, efficient, and user-friendly solution suitable for real-world agricultural environments

Software Specifications

The software components used in this project are:

Backend / AI Model Development

• Python 3.8+

• TensorFlow/ Keras

• NumPy

• OpenCV • scikit-learn

• Pillow ModelDeployment

• TensorFlow Lite Converter

• TFLiteInterpreter Mobile Application

• React Native • React Native CLI / Expo

• Android Studio (for building APK)

• Java / GradleBuild System Tools Used

• VS Code

• Jupyter Notebook

• Android Emulator (optional)

Hardware Specifications For Model Training-

• Processor: Intel i5/i7 or equivalent

• GPU (optional but recommended): NVIDIA GPU

• RAM: Minimum 8GB (16GB recommended)

• Storage: Minimum10GBfree space For Mobile App (User Side)

• Android Smartphone • RAM: Minimum 2GB

• Storage: 200MB available • WorkingCamera

• Android Version: 7.0 (Nougat) or above For Testing

• Any modern Android device with camera support

• USBcable (for APK installation, if not downloaded directly)

4. Results and Discussion

The proposed IoT-integrated machine learning system was evaluated based on its accuracy, performance, and usability in real-world agricultural scenarios. The crop yield prediction model demonstrated high accuracy by effectively analyzing environmental parameters such as soil moisture, temperature, humidity, and rainfall. The integration of IoT sensors enabled continuous data collection, which significantly improved prediction reliability compared to traditional methods.

For disease detection, the MobileNetV2 deep learning model achieved efficient classification performance across multiple crop categories. The model provided accurate predictions with minimal computational requirements, making it suitable for mobile deployment. After conversion to TensorFlow Lite, the model size was significantly reduced, allowing fast inference with a response time of less than one second on standard Android devices.

The system was also evaluated using performance metrics such as accuracy, precision, and recall, where it showed consistent and reliable results. Compared to existing cloud-based systems, the proposed solution offers several advantages, including offline functionality, reduced latency, and improved accessibility for farmers in rural areas.

Overall, the results indicate that the integration of IoT and machine learning provides an effective and practical solution for smart agriculture. The system not only enhances prediction accuracy but also improves usability, making it a scalable and efficient tool for real-world agricultural applications.

5. Conclusion

Agriculture remains the cornerstone of food security and economic stability, yet farmers continue to face challenges in predicting crop yield and detecting plant diseases due to dynamic environmental conditions, limited expertise, and lack of timely interventions. This project addressed these challenges by designing and implementing an IoT-integrated machine learning model that combines real-time sensor data with deep learning techniques to provide accurate, farmer-friendly predictions. The system leverages IoT sensors to continuously monitor key agricultural parameters such as soil moisture, temperature, humidity, rainfall, and nutrient levels. These data streams are preprocessed and analyzed using machine learning algorithms to estimate crop yield with improved accuracy. In parallel, lightweight deep learning models such as MobileNetV2 optimized with TensorFlow Lite were employed for disease detection from leaf images, enabling offline, real-time inference on mobile devices. This dual approach ensures that farmers receive actionable insights both on crop health and expected productivity. The results of the project demonstrate that integrating IoT with machine learning significantly enhances prediction reliability compared to traditional methods. Evaluation metrics such as accuracy, precision, recall, and F1-score confirmed the robustness of the proposed models. Moreover, the mobile application developed using React Native provides an intuitive interface for farmers, allowing them to capture leaf images, view disease classifications, and receive yield predictions instantly—even in rural areas with limited internet connectivity. Beyond technical achievements, the project contributes to the broader vision of smart agriculture by promoting sustainable farming practices, optimizing resource usage, and reducing economic risks for farmers. The system can be scaled to support diverse crops and regions, making it a practical solution for modern agricultural challenges.

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