A Data-Driven Approach to Sustainable Farming Using Random Forest and CNN-Based Model

Dr. M. Swapna
Assistant Professor
Computer Science and Engineering Department
Matrusri Engineering College
Saidabad, Hyderabad, Telangana, India

Abstract:

Agriculture is the main aspect for the economic development of a country. The increasing demand for sustainable agriculture and food security has driven research into intelligent, datadriven decision farming systems. This paper focuses on building a system to support the integration of artificial intelligence to improve fertilizer recommendations, crop recommendations and crop diseases. The system uses supervised machine learning and deep learning techniques to optimize farming decisions based on environmental and crop-specific factors. The fertilizer and crop prediction modules utilize a supervised machine learning approach, employing the Random Forest technique on structured datasets. The fertilizer dataset includes over 100 records with features like soil nutrients (N, P, K), soil type, and crop type, while the crop prediction dataset contains over 2,200 entries including temperature, pH, rainfall, and humidity. Data preprocessing involved handling missing values, normalization, and label encoding. The Random Forest model achieved high accuracy demonstrating strong predictive performance. For disease detection, a deep learning model based on CNN is trained on a dataset of over 50,000 labeled images of healthy and diseased crop leaves and the name of the disease. The model achieved high classification accuracy and robustness across various crop types. This paper incorporates a user-friendly web interface, enabling farmers to efficiently provide input data and receive real-time, actionable recommendations. The adoption of this methodology fosters the advancement of sustainable and cost-effective agricultural practices.

Keywords: Leaf image classification, Fertilizer Recommendation, Crop Disease Prediction, Machine Learning in Agriculture, Deep Learning for Agriculture, Data Driven Farming, Crop Management.

1. INTRODUCTION:

Agriculture stands as one of the most essential pillars for sustaining human life, underpinning not only food production but also the livelihoods of a significant proportion of the global population. Particularly in regions where rural communities dominate the demographic landscape, agriculture continues to play a central role in economic development and societal well-being. Rapid population growth, crop selection, erratic climate conditions, and soil degradation have compounded the difficulties faced by farmers in achieving consistent and sustainable yields. Despite advances in agricultural machinery and access to digital tools, a large segment of smallholder farmers continues to depend on personal experience and traditional practices when making critical farming decisions. Recent strides in artificial intelligence (AI) and machine learning (ML) have unlocked powerful capabilities for addressing longstanding inefficiencies in agricultural systems. Through data driven analysis, AI has demonstrated promise in refining key farming practices such as crop recommendation, fertilizer planning, and plant health assessment. This technological transformation offers an opportunity to shift decision-making from guesswork to precision, enabling farmers to respond proactively to environmental and agronomic variables. This paper serves as an intelligent support platform that delivers real time recommendations across the agricultural cycle, drawing upon a blend of scientific data, machine learning models, and disease prediction, each designed to address a specific area of need within the farming process. The crop recommendation module leverages data such as soil nutrient content (including nitrogen, phosphorus, and potassium levels), pH value, temperature, rainfall, and humidity to suggest the most suitable crops for cultivation. Using supervised classification models trained on diverse datasets, the system identifies crops that are most likely to perform well under given conditions. Fertilizer optimization is another critical area where this paper offers substantial value. Instead of relying on generalized guidelines or other, the platform employs a machine learning model specifically, a Random Forest classifier to analyze soil nutrient profiles and predict the appropriate type of fertilizer to be used. The model is trained on a structured dataset that includes key input variables such as nitrogen (N), phosphorus (P), and potassium (K) concentrations, soil pH level, temperature, humidity, and moisture content. The target output consists of fertilizer categories, including organic, urea, DAP (di-ammonium phosphate), and others, depending on the nutrient deficiency or surplus identified in the soil sample. In practical terms, the system classifies each instance by evaluating the relationship between soil nutrient levels and crop nutrient requirements, then suggesting a fertilizer class that best aligns with optimal growing conditions. The Random Forest model's ensemble nature ensures high accuracy and robustness against overfitting, especially when dealing with diverse agricultural inputs. A key innovation of the system lies in its capability for plant disease detection through image-based analysis. Utilizing a convolutional neural network architecture specifically the lightweight and efficient MobileNet model the platform can accurately classify plant leaves as either healthy or diseased. The model has been trained on a diverse image dataset covering multiple crop species and a wide range of user inputs. The platform is structured around three core functionalities: crop recommendation, fertilizer optimization, and disease conditions, enabling it to perform reliably even with lower-resolution images or those taken under varying environmental conditions. Nonetheless, like any technological solution, this is not without its current limitations. One of the primary challenges is the system currently offers qualitative fertilizer suggestions, future iterations may include quantitative recommendations to support more precise agricultural planning, the other is reliance on publicly available datasets, which may not fully represent local variations in soil properties, crop strains, or disease manifestations. As such, ongoing efforts are needed to incorporate region-specific data and field-level feedback to further enhance model Accuracy. Looking ahead, the paper aims to evolve through continuous learning and integration of advanced data sources, such as satellite imagery, geolocation services, and sensor-based field data. Collaborations with agricultural experts, local farmers, and agronomists will be instrumental in refining the system and extending its real-world impact. The goal is not only to offer a technological tool but to create a meaningful bridge between traditional farming wisdom and modern computational intelligence.

2. LITERATURE SURVEY:

1. Crop Disease Identification and Fertilizer Recommendation System (IRJMETS, Nov 2024):

This research presents a web-based agricultural decision-support platform developed using the MERN stack. The system utilizes Convolutional Neural Networks (CNNs) to process plant leaf images for disease identification and Natural Language Processing (NLP) to analyze textual symptom inputs provided by farmers. It uniquely combines these modalities to ensure accurate disease detection across diverse input types. Upon identifying a disease, the platform suggests customized fertilizer recommendations tailored to the crop type, disease diagnosed, and specific soil conditions. The application also includes email-based alerts and location-aware notifications, improving real-time communication and regional awareness among farmers. While the study does not report quantitative accuracy results, it emphasizes the system's effectiveness in delivering targeted agricultural advice and supporting sustainable farming practices through AI integration.

2. **ML-Based Flutter Application for Smart Agriculture (IJERCSE, June 2024)**:

This study introduces a mobile-based application built using the Flutter framework to support smart farming through disease detection and NPK nutrient prediction. It incorporates MobileNet, trained on a dataset of over 87,000 images across 38 plant disease categories, for efficient and real-time leaf disease recognition. In parallel, it employs a Random Forest Regression model, which predicts Nitrogen, Phosphorus, and Potassium levels using soil features like pH, temperature, humidity, and rainfall. The NPK model was optimized through k-fold cross validation and achieved up to 87% accuracy in predicting nitrogen content. The app accepts user input through direct image capture or upload, and generates both disease information and fertilizer recommendations based on current crop and location data. Designed for compatibility with low-end smartphones, the system promotes accessibility and precision agriculture for farmers in rural areas.

3. Leaf Disease Detection and fertilizer Recommendation using Deep Learning (2023):

The 2023 study titled "Leaf Disease Detection and Fertilizer Recommendation using Deep Learning" focuses on applying deep learning techniques to enhance agricultural disease management. Although the authors and institutional affiliations are not provided, the paper introduces a system that uses Convolutional Neural Networks (CNN) to analyze leaf images and identify plant diseases with a reported accuracy of 92%. The primary goal is to automate the detection of visual symptoms such as color changes and leaf damage, which are early indicators of diseases. After detecting the disease, the system suggests suitable fertilizers based on the plant type and condition, making it a dual-function model. This integration of disease diagnosis and remedy recommendation aims to reduce manual effort, improve crop health, and enhance yield. The study demonstrates how deep learning can be effectively applied to practical agricultural challenges by offering a reliable and user-friendly solution for farmers. While it lacks institutional backing in the available document, the approach shows significant promise for real-world deployment in smart farming environments.

4. Sustainable Farm Management Using Machine Learning by Krishna, Padhy, and Patnaik (GIET University, 2024)

In 2024, P. Ankit Krishna, Neelamadhab Padhy, and Archana Patnaik from the Department of Computer Science and Engineering, GIET University, Gunupur, Odisha, published a comprehensive research paper titled *"Applying Machine Learning for Sustainable Farm Management: Integrating Crop Recommendations and Disease Identification"*. Their work introduces a hybrid model that leverages IoT sensor data and advanced machine learning algorithms to provide intelligent crop and disease management recommendations. Real-time data such as NPK values, temperature, humidity, pH, and rainfall were collected and analyzed using ML models like Random Forest, XGBoost, and Gaussian Naive Bayes, which yielded a remarkable 99% accuracy in crop recommendation tasks. For disease identification, the researchers employed stateof-the-art CNN architectures—VGG16 (95.75%), ResNet50(96.06%), and EfficientNet V2(97.12%) to classify leaf images. The solution was implemented through a Flask-based web application, allowing farmers to input field data or upload leaf images and receive immediate, accurate feedback. By combining sensor inputs with deep learning, the system offers a robust, scalable platform for precision agriculture, demonstrating a successful integration of technology into realworld farming practices.

5. Improved MobileNetV2 Crop Disease Identification Model for Intelligent Agriculture by Jianbo Lu et al. (2023):

Jianbo Lu and his team proposed an enhanced version of the MobileNetV2 model to improve crop disease detection for intelligent agriculture applications.The model integrates a Reparameterized Multilayer Perceptron (RepMLP) to enhance global feature extraction and an Efficient Channel Attention (ECA) mechanism to focus on important feature channels. These additions improve both accuracy and computational efficiency. The model was evaluated using the PlantVillage dataset, which contains a wide range of diseased and healthy crop leaf images. It achieved an accuracy of 99.53%, surpassing the baseline MobileNetV2 by 0.3%. Additionally, the improved model reduced parameters by 59%, bringing the total to just 0.9 million, and increased inference speed by 8.5%. These improvements make it highly suitable for deployment on mobile and edge devices. The research supports real-time, onsite disease detection, offering farmers a practical AI-based solution for managing crop health efficiently.

3. EXISTING SYSTEMS:

Demonstrated effective real-time crop and fertilizer recommendations; improved decision making at field level Current agricultural support systems often utilize isolated machine learning models to address specific challenges such as crop recommendation, fertilizer management, or disease detection. While these systems demonstrate progress in digitizing agricultural practices, they typically lack integration and adaptability across diverse conditions. Some systems focus solely on crop prediction using logistic regression or decision trees trained on environmental and soil parameters. Others implement fertilizer recommendation models that suggest nutrients based on basic soil metrics but fail to account for crop-specific needs or real-time environmental fluctuations. Plant disease identification is frequently addressed using convolutional neural networks (CNNs), particularly architectures like ResNet or VGG, often trained on benchmark datasets, while effective in controlled conditions, these models often underperform when deployed in field scenarios due to image noise, occlusion, or low lighting. Moreover, existing platforms tend to operate in isolation offering solutions for either crop prediction, disease detection, or fertilizer advice independently without a cohesive framework that combines all three.

4. PROPOSED SYSTEM:

The proposed system integrates comprehensive end-to-end data processing workflows, including data collection, preprocessing, model development, validation, and deployment. By combining advanced machine learning and deep learning techniques, it delivers a unified, scalable, and interpretable decision support framework. This integrated platform effectively tackles key

Challenges such as optimized crop recommen dation, precise fertilizer management, and accurate disease detection, thereby enhancing farm productivity and promoting sustainable agricultural practices.

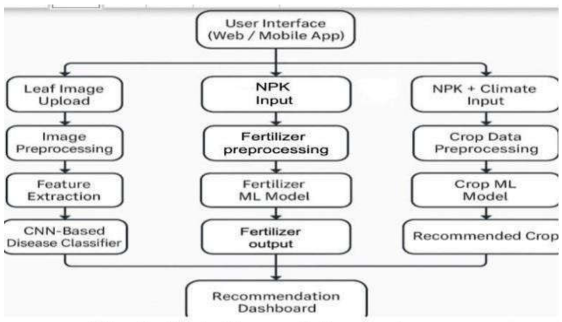

Fig 1: Dataflow of the system

4.1 Data Collection: This paper utilizes multiple datasets encompassing key agronomic and pathological features essential for accurate agricultural recommendations. The crop recommendation dataset comprises around

2,000 records with features such as soil nutrient levels—Nitrogen (0–140 ppm), Phosphorus (5– 145 ppm), Potassium (50–300 ppm)—soil pH (4.5–8.5), temperature (10– 40°C), rainfall (20– 300 mm), and relative humidity (30–90%). These variables are interrelated, soil pH influences nutrient availability, while temperature and rainfall affect water absorption and crop growth. Each entry is labeled with the most suitable crop for the given soil and climatic conditions, supporting machine learning models like Random Forests in predicting optimal crop choices. For fertilizer recommendation, the system employs a dataset with over 1,000 samples containing soil nutrient contents (N, P, K), soil texture (e.g., sandy, clayey, black), crop types like Maize, Sugarcane, Cotton and more, and corresponding fertilizer like Urea, DAP (Diammonium Phosphate), 14-35-14. The interplay between soil nutrients and texture informs fertilizer suitability, enabling the model to suggest appropriate fertilizer types to correct nutrient imbalances and enhance soil health. The plant disease detection dataset, features approximately 54,000 annotated images across various crops. Focusing on corn, the dataset includes 15 classes like Pepper bell Bacterial spot, Potato healthy, Tomato Leaf Mold, Tomato Yellow Leaf Curl Virus, Tomato Bacterial spot and more. Each image captures disease symptoms under diverse environmental conditions.

4.1 Data Preprocessing:

Noisy datasets can reduce the accuracy and reliability of machine learning models. Effective data preprocessing, such as cleaning and normalization, helps mitigate this issue. These steps enhance the model's ability to learn meaningful patterns and generalize better. In this system, several preprocessing techniques are applied to ensure the quality and consistency of input data across all modules. One fundamental step is handling missing or null values, which are either imputed using statistical methods (e.g., mean or mode substitution) or removed if they fall below a significance threshold. This minimizes data sparsity and prevents biased learning. For categorical features such as soil texture and crop type, label encoding or one-hot encoding is employed to convert textual data into machine-readable numerical formats. Numerical features such as temperature, pH, and nutrient levels are normalized or standardized to ensure uniform scaling, which aids in faster convergence during training. In the image-based disease detection module, data preprocessing includes resizing images to a fixed resolution, converting them to grayscale or RGB format as required, and applying normalization to pixel values. Additionally, data augmentation technique such as rotation, flipping, and zooming are used to increase dataset diversity and improve the model's robustness against overfitting. By integrating these preprocessing techniques, the system ensures the datasets are clean, consistent, and suitable for training high performance models across all prediction tasks.

4.2 Architecture Model

A. **Fertilizer Recommendation**: The fertilizer recommendation module utilizes machine learning to provide data-driven crop selection based on user inputs. Fertilizer recommendation involves determine the optimal type of fertilizer required to balance soil nutrients and enhance crop yield. In the system, this module utilizes key soil parameters such as Nitrogen (N), Phosphorus (P), Potassium (K) levels, soil texture, and crop type as inputs. The model predicts the most suitable fertilizer among seven categories in the dataset: Urea, DAP, 14-35-14, 28-28, 17-17-17, 20-200, and 10-26-26. While 20% of the dataset was used for validation and testing, the remaining 80% was allocated for training models. Various machine learning models, including Random Forest and Linear Regression, SVC, KNN, were evaluated, with Random Forest delivering accuracy 99.3% and robustness. This enables precise fertilizer recommendations that support efficient nutrient management

B. Crop Recommendation: In this paper , the crop recommendation module operates by receiving a structured set of environmental and agronomic inputs provided by the user. These inputs include soil nutrient concentrations—Nitrogen (N), Phosphorus (P), and Potassium (K)—measured in parts per million (ppm), as well as soil pH, ambient temperature (°C), rainfall (mm), and relative humidity (%). Upon submission, this data is processed by a machine learning model specifically a Random Forest classifier trained on a labeled dataset comprising approx 2,000 records. While 20% of the dataset was used for validation and testing, the remaining 80% was allocated for training models. It supports classification across 22 crop types, including rice, maize, chickpea, kidney beans, pigeon peas, black gram, lentil, pomegranate, banana, mango, grapes, watermelon, apple, orange, papaya, coconut, cotton, jute, and coffee. This datadriven approach enables precise crop selection, contributing to improved productivity and resource optimization in diverse agricultural settings. Various machine learning models, including Random Forest and Linear Regression, were evaluated, with Random Forest delivering superior accuracy 99.3% and robustness.

C. Crop Disease Prediction: Convolutional Neural Networks (CNNs) represent a transformative innovation in the realm of artificial intelligence and computer vision. At their core, CNNs are specialized deep learning architectures meticulously crafted to tackle complex visual recognition tasks, making them exceptionally adept at processing images and extracting meaningful features. The crop disease prediction module, a convolutional neural network (CNN) architecture is employed to classify plant diseases from leaf images. The model begins with an input layer that accepts RGB images of size 224×224×3. The first processing layer is a convolutional layer (Conv1), which applies 32 filters to extract lowlevel features such as edges and textures. This is followed by a batch normalization layer that normalizes the activations to stabilize and speed up training. The output then passes through a ReLU activation function, introducing non-linearity into the model. Subsequently, a depthwise convolutional layer is applied to efficiently capture spatial features while reducing computational complexity.

Another batch normalization layer and a ReLU activation follow, continuing the feature refinement. This structure aligns with a lightweight CNN backbone, inspired by MobileNet, designed for high efficiency and accuracy. The model leverages transfer learning by utilizing a pretrained MobileNet architecture trained on ImageNet and fine-tuned using the dataset, which contains labeled images of healthy and diseased crop leaves. This enables the model to generalize effectively across multiple disease categories. The final layers include fully connected layers and a softmax output that classifies the input image into specific disease categories.

5. RESULTS

5.1 INPUTS: Input data serves as the fundamental basis for all analytical processes and model development. Consequently, wellprepared input data directly influences the reliability and effectiveness of the model's predictions.

i) Input for Crop Disease Prediction: The input consists of clear, high-quality images of crop leaves showing visible disease symptoms. These images are submitted through a user-friendly interface, enabling the system to analyze leaf patterns for accurate disease identification.

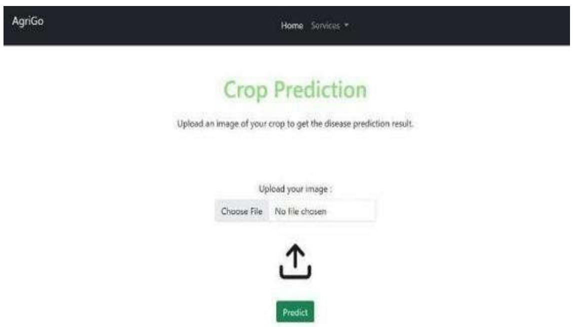

Fig 2: Input for crop disease prediction

ii) **Input for Fertilizer Recommendation:** The fertilizer recommendation system takes key inputs like values of soil temperature, humidity, mosture etc to provide accurate, need-based suggestions.

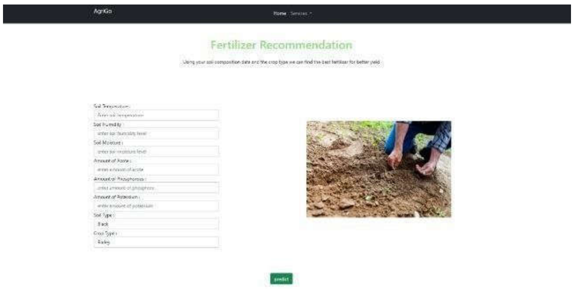

Fig 3: Input for fertilizer recommendation

iii) Input for Crop Recommendation:

The crop recommendation system evaluates field conditions and environmental factors to suggest the most suitable crops for a given region.

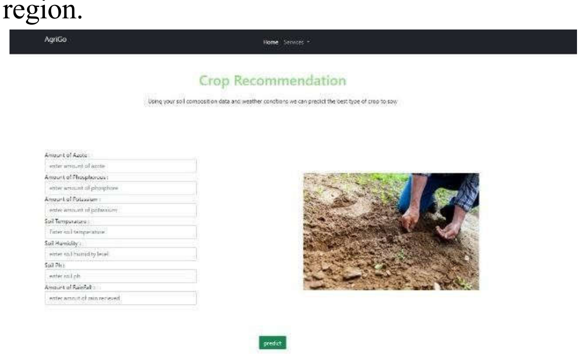

Fig 4: Input for crop recommendation

5.2 RESULTS:

Output data represents the results generated by the model after processing the input. It reflects the model's ability to interpret and analyze the given data accurately.

i) **Output for Crop Disease Prediction:** The system accurately identified plant diseases with over 93% accuracy using leaf image analysis. The model was able to distinguish between multiple disease categories, demonstrating robust classification capabilities.

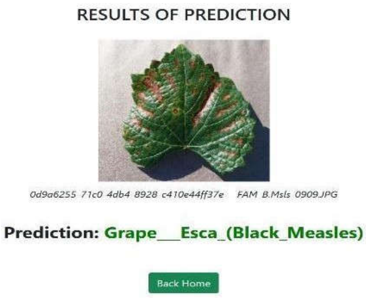

Fig 5 : Output for Crop disease prediction

ii) **Output for Fertilizer Recommendation:** The system provided precise fertilizer suggestions tailored to specific soil and crop conditions, enhancing nutrient management. This personalized approach helps optimize crop growth while minimizing excessive fertilizer use, promoting sustainable agricultural practices.

Fig 6: Output for fertilizer recommendation

iii) **Output for Crop Recommendation:** The system successfully recommended suitable crops based on soil properties and climatic conditions, achieving an accuracy of over 99%. These recommendations assist farmers in selecting the most appropriate crops for their land, thereby improving yield potential and resource efficiency.

Fig 7: Output for crop recommendation

5.3 GRAPHS

i) The graph displays the accuracy of different machine learning models used for fertilizer recommendation. The Random Forest model performs the best with an accuracy of 99.32%, making it the most effective among the tested models. K-Nearest Neighbors (KNN) also performs well with 99.01% accuracy. In comparison, Logistic Regression and SVC achieved 91.36% and 90.02% respectively, showing slightly lower performance.

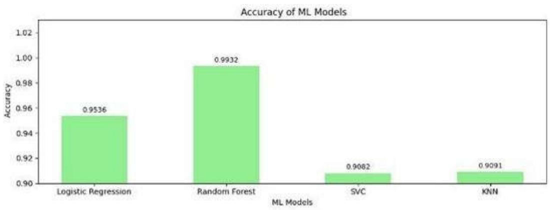

Fig 8: Accuracy of fertilizer recommendation model

ii) This bar chart shows the accuracy of different machine learning models used for crop recommendation. The Random Forest model achieved the highest accuracy of 99.32%, making it the most effective option. K-Nearest Neighbors (KNN) also showed strong results with an accuracy of 99.01%. The Support Vector Classifier (SVC) reached 96.82%, while Logistic Regression had the lowest accuracy of 96.36%. All models performed well, but Random Forest proved to be the most accurate and reliable choice for this task.

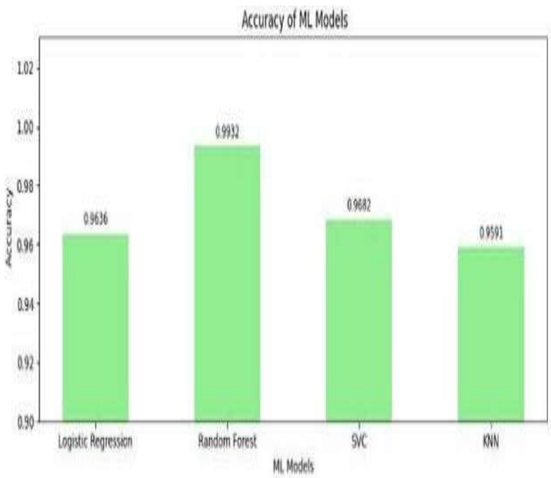

Fig 9: Accuracy of ML Models for crop recommendation

iii)

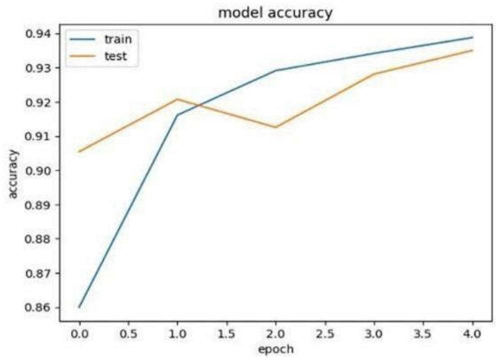

Fig 10: Crop Disease Prediction Model Accuracy graph

This line graph illustrates how the training and testing accuracy of a crop prediction model change across several epochs. The training accuracy (blue line) gradually rises from about 86% to nearly 94%, showing steady improvement. The testing accuracy (orange line) also increases, reaching close to 93% by the last epoch. Both curves follow an upward trend, indicating effective learning. The small difference between the two suggests that the model generalizes well with minimal signs of overfitting.

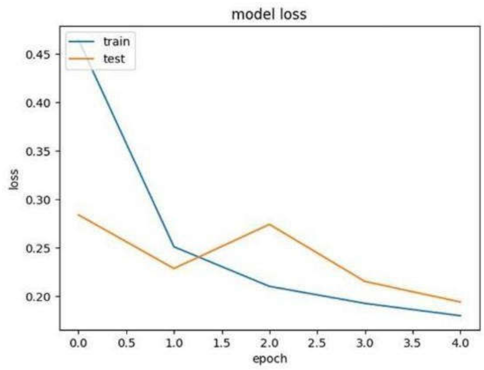

Fig 11: Crop Disease prediction Model Accuracy Loss graph

This graph displays the variation in training and testing loss for a crop prediction model over five epochs. The training loss starts at a higher value and steadily decreases, showing improved model performance with each epoch. The testing loss also reduces overall, though it shows a slight increase around the second epoch before continuing to fall. By the end, both loss values are low, indicating that the model is successfully minimizing errors and learning efficiently from the data.

6. CONCLUSION

The transformative role of technology in promoting sustainable and efficient agricultural practices cannot be overstated in today's evolving agronomic landscape. This paper affirms the critical value of intelligent, data driven systems for crop and fertilizer recommendation, tailored to local environmental and agronomic conditions. The selected models—such as CNN for disease prediction, Random Forest for crop recommendation, fertilizer recommendation were chosen for their proven effectiveness in handling complex agricultural datasets. CNN excels in image-based classification, making it ideal for detecting plant diseases from leaf images. Random Forest is well-suited for crop recommendation due to its high accuracy, robustness, and ability to handle non-linear relationships in soil and climate data. Random Forest offers reliable performance in fertilizer prediction by efficiently classifying data based on multiple nutrient and environmental parameters. Our research encompassed extensive experimentation with convolutional neural networks, leveraging transfer learning through a fine-tuned MobileNet model trained on an augmented multi-class dataset comprising plant leaf images. Through rigorous preprocessing steps including class balancing, normalization, and noise reduction, we enhanced the model's robustness and minimized data-induced bias. Model evaluation involved metrics such as Accuracy and Confusion Matrix visualization to gauge classification efficacy across 38 plant disease categories. The MobileNet based classifier achieved high performance that is 93.3 %, which is suitable for this paper. In the crop recommendation module, supervised machine learning algorithms were trained on regionspecific agronomic and environmental data, including soil composition (pH, moisture, NPK values), rainfall patterns, and temperature profiles. These features were mapped to crop suitability using ensemble classifiers, enabling the system to provide context-aware, crop recommendations. The fertilizer recommendation system further complements this functionality by employing random forest based models to suggest optimal nutrient application strategies tailored to crop type and soil nutrient levels. This enables precision nutrient management, thereby enhancing yield potential while promoting sustainable input usage. In summary, this paper stands as a comprehensive intelligent agricultural assistant that leverages modern AI methodologies to support sustainable farming. Future research should prioritize adaptive learning models and IoT-based data integration to enhance predictive scalability across diverse geographies and crop variants.

7. REFERENCES

[1]. Rahim, R., & Wahid, A. (2023, August). Advancements in Plant Disease Detection: Integrating Machine Learning, Image Processing, and Precision Agriculture. International Journal of Computer Engineering in Research Trends.

[2]. Ganesh, N. B. (2025, January). Plant Disease Detection by Image Processing. International Journal of Scientific Research in Engineering and Management.

[3]. Jadhav, S.B.; Udupi, V.R.; Patil, S.B. Identification of plant diseases using convolutional neural networks. Int. J. Inf. Technol. 2021, 13, 2461–2470.

[4]. A. Barman, S. Shome, M.J. Alam, S. Akhter, and M.A. Hossain. Fertilizer recommendation for four crop based cropping pattern: Potato- boro-t. aus-t. aman under aez – 11. volume 22, pages 71 78, 2019.

[5]. Fuentes, A.; Yoon, S.; Kim, S.C.; Park, D.S. A Robust Deep-Learning-Based Detector for Real Time Tomato Plant Diseases and Pests Recognition. Sensors 2017, 17, 2022

[6]. Rasal, S. R., & Co-authors. (2025, March).

Plant Disease Detection using IoT. International Journal of Advanced Research in Science, Communication and Technology.

[7]. Athani, S.S.; Tejeshwar, C.H. Support Vector Machine-Based Classification Scheme of Maize Crop. Int. J. Comput. Appl. 2017

[8]. Zhong, Y.; Zhao, M. Research on deep learning in apple leaf disease recognition. Comput. Electron. Agric. 2020, 168, 105146.

[9]. N. Gandhi, L. J. Armstrong, O. Petkar and A. K. Tripathy, “Rice crop yield prediction in India using support vector machines” 2016 13th International Joint Conference on Computer Science and Software Engineering (JCSSE), KhonKaen, 2016, pp. 1-5.

[10]. Prity, F.S., Hasan, M.M., Saif, S.H. et al. Enhancing Agricultural Productivity: A Machine Learning Approach to Crop Recommendations. Hum-Cent Intell Syst 4, 497–510 (2024).

[11]. Burdett, H., & Wellen, C. (2022). Statistical and machine learning methods for crop yield prediction in the context of precision agriculture. Precision agriculture, 23(5), 15531574.

[12]. Pandit, A., et al, “IoT-based crop & fertilizer recommendation system using machine learning”, Information Technology, PVG’s COET, Pune, India, 2023.