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Crop Recommendation System Based on Productivity Using Machine Learning Algorithm

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Abstract

Tamil Nadu, being a coastal state, faces uncertainty in agricultural production due to frequent climatic variations and environmental changes. Although the state has a large cultivable area and a growing population, the expected level of productivity has not been achieved. In earlier decades, farmers relied mainly on traditional knowledge and word-of-mouth practices for crop cultivation, but these methods have become unreliable under present climatic conditions. Agricultural activities depend on factors such as rainfall, temperature, soil characteristics, humidity, and seasonal variations, which generate large volumes of data. The rapid growth of information technology has created new opportunities in agricultural sciences by enabling effective data analysis. In this context, modern computational and machine learning techniques play an important role in extracting insights from agricultural data. These techniques support prediction and decision-making for challenges such as crop selection, crop rotation, water requirement estimation, and fertilizer usage. Due to dynamic environmental conditions, efficient systems are needed to support farmers. This study highlights the role of data analytics in developing a crop recommendation system that suggests suitable crops based on climatic conditions, productivity, and seasonal factors.

Keywords— Crop Recommendation System, Machine Learning, Data Analytics, Climatic Factors, Precision Agriculture

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1.Introduction

Agriculture remains one of the most essential sectors in India, playing a key role in food production, employment generation, and economic stability. Tamil Nadu is a prominent agricultural state, ranking seventh in terms of geographical area and sixth in population. A large segment of the population relies on agriculture as its primary source of livelihood. The state is known for cultivating major crops such as rice, sugarcane, cotton, coconut, and groundnut. Rice cultivation is especially significant in the Cauvery delta region, which is widely recognized as the rice bowl of Tamil Nadu. Agriculture not only supports rural communities but also contributes substantially to the overall economic development of the state and the country [1]. A crop recommendation system considers nitrogen, phosphorus, potassium, temperature, humidity, soil pH, and rainfall because successful crop growth depends on a proper balance of soil nutrients and climatic conditions. Nitrogen supports healthy leaf growth and photosynthesis, phosphorus helps in root development and energy transfer, and potassium improves plant strength and resistance to diseases. Temperature and humidity influence seed germination, growth rate, flowering, and water loss from plants, ensuring the crop can complete its life cycle under suitable environmental conditions. Soil pH plays a vital role in nutrient availability, as unsuitable pH levels can prevent plants from absorbing nutrients even when the soil is fertile. Rainfall determines the natural water supply to crops and helps in selecting crops that can thrive under either high or low water availability. By analyzing all these parameters together, the crop recommendation system provides accurate and reliable suggestions that help farmers select the right crop, improve productivity, and reduce the risk of crop failure.

In recent years, agricultural productivity has faced serious challenges due to rapid changes in climatic and environmental conditions. Crop growth is influenced by multiple factors, including rainfall, soil characteristics, temperature, humidity, sunlight, fertilizers, and pest control practices. India experiences four distinct seasons—winter, summer, monsoon, and post-monsoon—and each season directly affects crop growth patterns. Uncertain rainfall and unpredictable weather conditions make it increasingly difficult for farmers to select suitable crops and accurately estimate yields, often resulting in reduced productivity and financial loss [2].

Traditionally, farmers depended on knowledge passed down through generations and local experience to make cultivation decisions. While such practices were effective in the past, they are no longer sufficient in the present scenario due to climate variability, soil degradation, and increased pest infestations. Farmers now face challenges such as inefficient crop selection, improper use of fertilizers, declining soil fertility, and uncertainty in yield prediction. These issues highlight the need for scientific, data-driven approaches to support farmers in making informed agricultural decisions [3].

The advancement of information technology has brought significant changes to modern agriculture. The adoption of technologies such as soil testing, weather monitoring systems, and digital record-keeping has resulted in the generation of large volumes of agricultural data. Analyzing this data manually is both time-consuming and impractical. Data mining techniques provide effective solutions by extracting useful patterns and insights from large agricultural datasets. Several studies have demonstrated that soil analysis using classification techniques helps identify soil suitability and recommend appropriate crops, leading to improved land utilization and productivity [4].

Weather-based data analytics has also gained importance in crop management. By analyzing historical and real-time weather data, farmers can plan irrigation schedules, manage fertilizer application, and reduce risks associated with adverse weather conditions. Such approaches help optimize resource usage while enhancing crop yield and sustainability [5].

Machine learning, a subfield of artificial intelligence, has emerged as a powerful tool for agricultural prediction and decision support. Unlike traditional statistical methods, machine learning algorithms can handle large datasets and capture complex, nonlinear relationships among agricultural parameters. Machine learning-based crop and yield prediction models assist farmers in selecting suitable crops, estimating expected yields, and improving farm management practices [1].

Recent research has explored advanced techniques such as neural networks for crop yield estimation. These models are capable of learning complex spatiotemporal patterns from environmental and image-based data, resulting in improved prediction accuracy. Furthermore, smart farming systems that integrate data mining and machine learning techniques offer real-time recommendations for irrigation, fertilizer usage, and pest management. Such intelligent systems play a crucial role in promoting precision agriculture and ensuring long-term agricultural sustainability [6], [7].

2.Literarture Review

With the increasing challenges faced by the agricultural sector, such as climate change, soil degradation, water scarcity, and fluctuating market demands, researchers have increasingly focused on intelligent and data-driven solutions to improve agricultural productivity. One of the earliest and most impactful applications of machine learning in agriculture is crop and yield prediction. Bhanose and Bogawar proposed a predictive model for crop and yield estimation using historical agricultural data, demonstrating that machine learning models can assist farmers in making informed decisions regarding crop selection and yield expectations [1]. Their work established a foundation for applying predictive analytics in agriculture.

The role of real-time data collection and analysis has been emphasized through the integration of wireless sensor networks and data mining techniques. Tripathy *et al.* presented a framework that combines sensor data with data mining algorithms to predict pest and disease outbreaks in crops. This approach enabled early detection and timely intervention,

significantly reducing crop losses and improving farm management efficiency [2]. Such studies highlight the importance of automated data acquisition systems in precision agriculture.
Soil characteristics play a critical role in determining crop suitability and yield potential. Palepu analyzed agricultural soil datasets using data mining techniques to classify soil properties and assess fertility levels [3]. This research demonstrated that soil-based analytics can improve land utilization and crop productivity. Similarly, Rajeswari and Arunesh applied classification techniques to soil data to identify suitable crops based on soil conditions, reinforcing the importance of soil analysis in agricultural decision-making [4].
Weather variability is another major factor influencing agricultural productivity. Swarupa Rani explored the impact of data analytics on crop management using weather data and showed that weather-driven models can assist farmers in optimizing irrigation, fertilizer usage, and planting schedules [5]. Incorporating climatic parameters into predictive systems was shown to reduce uncertainty and improve crop yield outcomes.
Advanced machine learning techniques have further enhanced agricultural prediction systems. Bose and Kasabov introduced spiking neural networks for crop yield estimation using spatiotemporal image time series data. Their approach captured complex temporal and spatial relationships, achieving higher accuracy than traditional methods [6]. Chandak developed a smart farming system based on data mining that integrates crop, soil, and environmental data to provide actionable recommendations to farmers [7].
Recommendation systems have emerged as effective tools for personalized agricultural decision support. Kumar and Dave proposed *KrishiMantra*, an agricultural recommendation system that suggests suitable crops based on location-specific and environmental parameters [8]. Their system demonstrated how recommendation engines can simplify decision-making for farmers. Latu highlighted the use of Geographic Information Systems (GIS) and visualization techniques to support sustainable agricultural development, emphasizing the importance of spatial data in resource planning and management [9].
Pattern discovery and trend analysis in agriculture have also been widely studied. Fathima applied data mining techniques to analyze crop patterns, helping identify regional trends and cropping behaviors [10]. Medar presented a comprehensive survey of data mining techniques for crop yield prediction, providing a detailed comparison of commonly used algorithms and their performance [11]. Ahamed and Mahmood applied predictive models to estimate annual crop yields and recommend crops across different districts, demonstrating the scalability of data mining approaches in large agricultural regions [12].
Further research by Bhanose expanded upon earlier crop prediction models, reinforcing the effectiveness of machine learning-based approaches for yield estimation [13]. Iorshase and Charles proposed a hybrid recommender system for agricultural products, combining multiple recommendation strategies to improve recommendation accuracy and relevance [14]. Their work highlighted the growing relevance of hybrid recommendation models in agriculture.
Foundational studies on recommender systems by Adomavicius and Tuzhilin provided a detailed overview of recommendation techniques and their future extensions, forming the theoretical basis for modern agricultural recommender systems [15]. Jain and Kumar discussed the application of recommendation engines in agriculture, emphasizing their potential to deliver personalized crop, fertilizer, and resource recommendations [16]. Shinde proposed a web-based recommendation system designed to assist farmers in crop planning and decision-making, highlighting the accessibility of digital platforms for agricultural support [17].
Recent comprehensive reviews have emphasized the broader role of machine learning in agriculture. Liakos *et al.* provided an extensive review of machine learning applications in agriculture, covering areas such as crop prediction, soil analysis, pest management, and precision farming [18]. Vaishnavi *et al.* discussed the role of data mining in recommendation systems, highlighting how intelligent recommendations can manage information overload and improve user decision-making across various domains, including agriculture [19].

Although existing studies demonstrate the effectiveness of machine learning, data mining, GIS, and recommendation systems in agriculture, many approaches focus on individual parameters such as soil, weather, or yield in isolation. This reveals a clear research gap for developing integrated crop recommendation systems that combine multiple agricultural factors into a unified framework. Addressing this gap can lead to more accurate recommendations, improved productivity, and sustainable agricultural development.

3.Methodology

3.1 Proposed System

The proposed methodology follows a structured and data-driven approach to develop an efficient crop recommendation system aimed at supporting farmers in decision-making. The first step involves collecting agricultural datasets related to crop production in Tamil Nadu. The dataset includes attributes such as crop name, district, season, cultivated area, year, and production quantity. These parameters are essential for understanding historical crop performance across different regions and seasons.

Data preprocessing is performed to improve data quality and reliability. This includes handling missing values, removing duplicate records, correcting inconsistencies, and normalizing numerical features. Preprocessing ensures that the dataset is suitable for machine learning analysis and improves the accuracy of the prediction model.

After preprocessing, relevant features influencing crop productivity are selected. Feature selection helps reduce data dimensionality while retaining meaningful information required for effective learning. The processed dataset is then divided into training and testing sets to evaluate model performance.

The Light Gradient Boosting Machine (LightGBM) algorithm is employed for training the model. LightGBM is chosen due to its high efficiency, fast training speed, and capability to handle large-scale datasets. The model learns complex relationships between seasonal patterns, regional characteristics, and crop productivity. Performance evaluation is carried out using historical data to validate the accuracy and robustness of the model before deployment.

3.2 System Architecture

Agricultural data is first collected from a database and passed to the feature extraction module. In this stage, relevant and meaningful attributes are selected to improve learning efficiency and reduce data complexity. The extracted features are then used in the training phase, where machine learning models learn patterns from the data.

To enhance model performance, the training process employs a transfer learning approach, which utilizes previously learned knowledge to improve accuracy and reduce training time. After training, the models are saved and prepared for deployment.

The saved models are integrated into the system to generate predictions, and model evaluation is carried out to identify the best-performing model. Finally, the optimal model is selected based on performance metrics and deployed for real-time usage, ensuring efficient and reliable decision support.

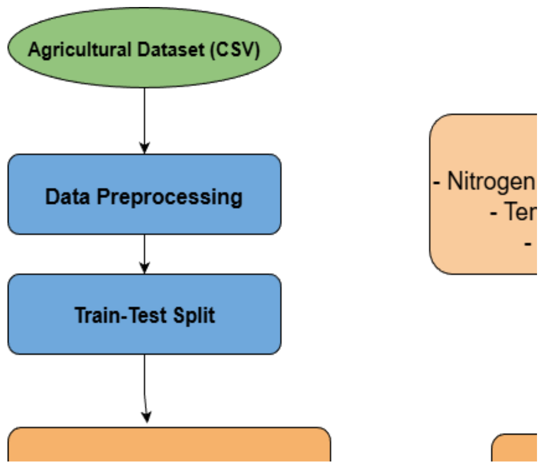

Fig 3.1 System Architecture

Fig 3.1 flowchart illustrates how the crop recommendation system works from start to finish. It begins with collecting an agricultural dataset in CSV format, which contains important soil and environmental information. The data then goes through preprocessing, where it is cleaned and prepared for analysis. After that, the dataset is divided into training and testing sets to ensure the model can learn effectively and make accurate predictions.

Next, the LightGBM model is trained using the prepared data. At the same time, the user provides input values such as nitrogen, phosphorus, potassium levels, temperature, humidity, soil pH, and rainfall. These user inputs are processed and passed into the trained model. Finally, based on both the learned patterns and the user's input data, the system predicts and recommends the most suitable crop. This ensures farmers or users receive data-driven guidance for better agricultural decisions

3.3 Dataset Collection

The dataset used in this study was collected from Tamil Nadu agricultural sources, including publicly available agricultural repositories and government-supported databases. These sources provide reliable and region-specific agricultural information that reflects real farming conditions in Tamil Nadu. The collected data represents various crops cultivated across different districts and seasons within the state, making it suitable for developing an accurate crop recommendation system.

The dataset consists of 22 distinct crop classes, representing major and commonly cultivated crops in Tamil Nadu. Each crop class contains approximately 200 records, ensuring a balanced distribution of data across all crop categories. This balanced dataset helps reduce bias during model training and improves the overall prediction performance.

Each record in the dataset includes essential agricultural attributes such as crop type, seasonal information, and related cultivation parameters. The availability of sufficient samples for each crop enables the machine learning model to effectively learn patterns and relationships between environmental conditions and crop suitability. As a result, the dataset forms a strong foundation for training, testing, and validating the proposed system.

3.4 Feature Selection

Correlation-Based Feature Selection (CFS) is employed to identify the most significant agricultural attributes that influence crop growth and productivity. This method evaluates the relationship between input features and crop labels, ensuring that only highly relevant features are retained while features with low correlation are eliminated. Key parameters such as soil nutrients, rainfall, temperature, humidity, soil pH, and seasonal conditions are selected, as they play a crucial role in determining crop suitability. Redundant and irrelevant attributes are removed to reduce noise in the dataset and improve learning efficiency. In addition, data transformation techniques such as normalization and encoding are applied to convert the selected features into a suitable numerical format for machine learning processing. By reducing feature dimensionality and eliminating unnecessary information, CFS decreases computational complexity and enhances the accuracy, robustness, and reliability of the LightGBM-based crop recommendation system.

3.5 Model Training

The training module forms the core of the proposed crop recommendation system, as it is responsible for learning meaningful patterns from the agricultural data and generating accurate predictions. In this stage, the pre-processed dataset is carefully divided into two subsets: a training set and a testing set. This separation is essential to ensure that the model learns from one portion of the data while being evaluated on unseen data, thereby avoiding overfitting and ensuring unbiased performance assessment. The training dataset contains historical agricultural records along with their corresponding crop labels and is used to train the machine learning model by learning the relationship between environmental factors and crop suitability. The testing dataset, which is not exposed to the model during training, is used to validate the model's generalization capability and measure its prediction accuracy under real-world conditions. This approach helps in assessing the robustness and reliability of the trained model, ensuring that it performs consistently across different agricultural scenarios and supports effective decision-making for crop recommendation.

3.5.1 Algorithm

Light Gradient Boosting Machine (LightGBM) is an efficient gradient boosting framework based on decision tree learning. It is designed to improve computational speed and reduce memory consumption while maintaining high predictive performance. Unlike traditional Gradient Boosting Decision Tree (GBDT) frameworks, LightGBM introduces two key optimization techniques: Gradient-based One Side Sampling (GOSS) and

Exclusive Feature Bundling (EFB), which significantly enhance training efficiency.
GOSS improves model performance by prioritizing data instances with large gradients, as these samples contribute more to information gain. Instances with smaller gradients are randomly sampled, ensuring accuracy is maintained while reducing computational cost. EFB further optimizes performance by combining mutually exclusive features into a single feature, effectively reducing dimensionality without information loss.

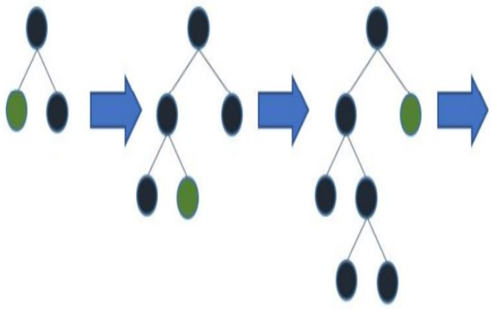

Fig 3.2 LightGBM Algorithm

Fig 3.2 illustrates a distinguishing characteristic of LightGBM is its leaf-wise tree growth strategy, in which the algorithm selects and expands the leaf node that results in the maximum reduction in loss at each iteration. Unlike traditional level-wise tree growth methods that expand all nodes at the same depth, the leaf-wise approach allows LightGBM to focus on the most informative splits. This results in faster convergence, deeper trees, and improved prediction accuracy, especially when dealing with complex and non-linear relationships among features. Although this strategy may increase the risk of overfitting, it can be effectively controlled using parameters such as maximum depth and minimum data in a leaf.

Parameter	Value
Learning Rate	0.05
Number of Leaves	31
Maximum Depth	-1
Number of Estimators	200

Table 1 Hyper parameter

The hyperparameters used in the LightGBM model are presented in Table 1. A learning rate of 0.05 was selected to ensure steady and controlled learning, helping the model gradually improve its predictions while avoiding overfitting. The number of leaves was set to 31 to manage the complexity of the decision trees and to effectively capture interactions among the agricultural features. The maximum depth was kept as -1, allowing the trees to grow freely and learn complex nonlinear relationships within the dataset. In addition, 200 estimators were used so that multiple trees could be built sequentially to reduce prediction errors through the boosting process. These values were determined through experimental testing to achieve consistent convergence and strong multi-class classification performance.
In the proposed crop recommendation system, LightGBM is used as the primary learning model to map environmental and soil parameters to suitable crop classes. Agricultural features such as soil nutrients, rainfall, temperature, humidity, soil pH, and seasonal conditions are provided as inputs to the model. During training, LightGBM learns intricate patterns between these factors and crop suitability by iteratively building decision trees using gradient boosting. Its ability to handle large datasets, missing values, and high-dimensional feature spaces makes it well suited for agricultural data analysis. Additionally, the algorithm's fast training speed and parallel learning capability enable efficient model deployment, allowing the system to generate accurate and timely crop recommendations that support farmers in making informed cultivation decisions.

4.Results And Discussion

The proposed crop recommendation system was tested using the Tamil Nadu agriculture dataset with nearly 4,400 records. Important factors such as crop type, season, cultivated area, and production were analyzed after preprocessing the data. The LightGBM model was trained to understand productivity patterns and recommend suitable crops.
The results show that the system performed very well, achieving an accuracy of 95.4%, which is better than commonly used machine learning models. This indicates that LightGBM is effective in handling large agricultural datasets and capturing complex relationships between crop and seasonal factors. From the analysis, crops like banana, paddy, sugarcane, and groundnut were found to give good and consistent yields over the years. Banana, in

particular, showed stable production throughout the year, making it a reliable crop for farmers regardless of season. The study also highlighted that crop yield changes significantly with the area cultivated, proving that land usage plays an important role in productivity. Overall, the results confirm that the proposed system can provide useful and practical crop recommendations. By using past production data, the system helps farmers choose crops with better yield potential and reduces uncertainty caused by changing climatic conditions**.** The user enters specific agricultural parameters such as nitrogen, phosphorus, and potassium levels in the soil, along with environmental factors like temperature, humidity, soil pH, and rainfall. These values represent the real-time conditions of the field. Once the information is provided, the trained LightGBM model analyzes the input data by comparing it with patterns learned from the dataset. Based on these conditions, the system predicts the most suitable crop for cultivation.

```
Enter Agricultural Parameters:
Nitrogen (N): 90
Phosphorus (P): 42
Potassium (K): 43
Temperature (°C): 20.87974371
Humidity (%): 82.00274423
Soil pH: 6.502985292000001
Rainfall (mm): 202.9355362

Recommended Crop: rice
```

Fig 4.1 Crop Recommendation

From the Fig 4.1 for the given inputs, the model recommends **rice**, indicating that the soil nutrients and environmental conditions are highly favourable for growing rice. This helps farmers make informed decisions and choose crops that are more likely to yield better results.

In this case, the soil has good nitrogen (90), which supports healthy leaf growth, and moderate phosphorus (42) and potassium (43), which help in strong root development and disease resistance. The temperature is around 21°C, which is comfortable for crop growth, and the humidity is high (82%), meaning the environment has enough moisture in the air. The soil pH is about 6.5, which is slightly acidic and ideal for many crops, especially rice. The rainfall is around 203 mm, indicating good water availability. When all these conditions are combined, they closely match the ideal growing requirements of rice, which needs fertile soil, plenty of water, high humidity, and moderate temperature. That is why the system recommends rice as the most suitable crop.

4.2 Performance Metrices

Table 1 Comparative Insights

Method Used	Accuracy (%)
Light GBM (Proposed model)	95.4
Random Forest	92.3
Decision Tree	90.2
Support Vector Machine (SVM)	89.7
K-Nearest Neighbours (KNN)	91.5
Naïve Bayes	88.6
Artificial Neural Network (ANN)	84.9
Linear Regression	85.6
Supervised ML Classifiers (Combined)	87.8
Predictive ML Models	88.4

Table 1 compares the accuracy of different machine learning models. The proposed LightGBM model achieves the highest accuracy of 95.4%,The proposed LightGBM model achieved an accuracy of 95.4% using 80:20 train-test split with 5-fold cross validation. outperforming all other methods due to its efficient gradient boosting and feature handling capability. Ensemble models such as Random Forest (92.3%) and Decision Tree (90.2%) show good performance but remain inferior to LightGBM. KNN (91.5%) performs better than SVM (89.7%), while Naïve Bayes (88.6%) and ANN (84.9%) exhibit relatively lower accuracy. Overall, the results confirm the effectiveness of the proposed LightGBM model for accurate classification.

4.3 Performance Evaluation Metrics

Accuracy

Accuracy represents the overall correctness of the classification model. It indicates how many samples are correctly classified by the system out of the total number of samples. A higher accuracy value implies better overall performance of the model

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

Precision

Precision measures how accurate the positive predictions made by the model are. It shows how many of the instances predicted as positive are actually correct, thereby reducing false positive errors.

$$Precision = TP / (TP + FP) \quad (2)$$

Recall

Recall measures the ability of the model to identify all relevant positive instances. It indicates how many actual positive cases are correctly detected by the system. A higher recall means fewer important cases are missed.

$$Recall = TP / (TP + FN) \quad (3)$$

F1-Score

The F1-Score provides a balanced evaluation of both precision and recall. It is calculated as the harmonic mean of precision and recall. A higher F1-Score indicates that the model achieves both high accuracy in prediction and effective identification of relevant instances.

$$F1 - Score = (2 * Precision * Recall) / (Precision + Recall) \quad (4)$$

Confusion Matrix

A confusion matrix is used to evaluate the performance of a classification model by comparing predicted class labels with actual labels. It summarizes correct predictions along the diagonal and misclassifications in the off-diagonal elements. The matrix helps identify true positives, true negatives, false positives, and false negatives, and serves as the basis for computing performance metrics such as accuracy, precision, recall, and F1-score.

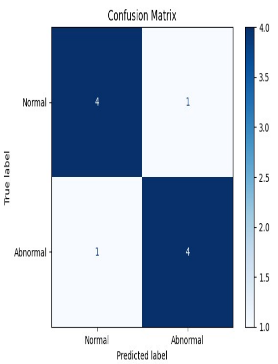

Fig 4.2 confusion matrix

Fig. 4.2 illustrates the confusion matrix obtained for the proposed classification model, where the performance is evaluated for two classes, namely *Normal* and *Abnormal*. The confusion matrix provides a detailed breakdown of correct and incorrect classifications made by the system. From the results, 4 Normal samples are correctly classified as Normal, while 1 Normal sample is misclassified as Abnormal. Similarly, 4 Abnormal samples are correctly classified as Abnormal, and 1 Abnormal sample is incorrectly classified as Normal. This indicates that the model is able to accurately identify the majority of both Normal and Abnormal cases.

The diagonal elements of the confusion matrix represent correct predictions, which are significantly higher than the off-diagonal elements that correspond to misclassifications. The relatively low number of false positives and false negatives demonstrates the robustness of the proposed model in distinguishing between Normal and Abnormal classes. Overall, the confusion matrix confirms that the proposed system achieves balanced classification performance with effective discrimination between the two classes, making it suitable for reliable decision-making in practical applications.

5. Conclusion and Future Work

This project successfully implements a machine learning–based crop recommendation system that helps identify the most suitable crop by analyzing soil nutrients and environmental conditions such as nitrogen, phosphorus, potassium, temperature, humidity, soil pH, and rainfall. The system accurately recommends rice when the given inputs match its ideal growing requirements, proving the effectiveness of data-driven approaches in agriculture. By guiding farmers in selecting the right crop, the system can improve productivity, reduce crop failure, and support sustainable farming practices. In the future, the model can be enhanced by integrating real-time weather updates, soil sensor data, and advanced machine learning or deep learning techniques for improved accuracy. Additional features such as fertilizer suggestions, pest and disease prediction, irrigation planning, and deployment as a mobile or web application with regional language support can further increase its practical usability and impact.

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