

Agricultural crop disease recommendation and leaf disease prediction

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Abstract - Agriculture is the backbone of many countries, including India, and provides livelihoods to millions of people facing challenges such as climate change and plant disease outbreaks. Through research, a web application has been developed that provides real-time recommendations for crop selection based on various factors such as soil nutrients, temperature, humidity, pH levels, and rainfall. Recent advances in machine learning and artificial intelligence offer promising solutions to these problems, enabling accurate, data-driven decision-making in agriculture. These technologies have the potential to transform how we predict crop yields and detect plant diseases, thus improving agricultural practices. To achieve this, we trained and examined seven machine learning models, Decision tree, Naive Bayes, SVM, Logistic Regression, Random Forest, XGBoost, and KNN. Among these, Random Forest gives the highest accuracy, making it the best choice for crop forecasting. In addition to crop recommendation, the web application also integrates a Plant Disease Identification system using Convolutional Neural Network (CNN). By analysing leaf images, CNN detects and accurately classifies plant diseases, allowing farmers to intervene early to prevent crop losses. This study aims to empower farmers with accessible technology to make informed decisions, improve crop selection, and effectively cure plant diseases. Combining crop recommendation with disease detection, intelligent crop recommendation systems with plant disease detection contribute to sustainable agriculture, economic stability, and food security in India and beyond.

Keywords - CNN, crop recommendation, machine learning, plant disease identification, random forest.

I. INTRODUCTION

The integration of machine learning and artificial intelligence (AI) technologies has ushered in a new era across various sectors, with agriculture emerging as a prominent beneficiary. Among the diverse applications of these technologies in agriculture, smart crop recommendations and plant disease identification stand out as pivotal advancements. Nowadays, the realm of machine learning and data science have revolutionized agricultural practices and one such innovation is the development of crop recommendation systems, which leverage predictive models to offer tailored guidance to farmers regarding the selection of crops best suited for their

specific soil and environmental conditions and crop disease detection using image classification techniques. In this paper, we present a comprehensive Crop Recommendation System implemented using Python, incorporating various machine learning algorithms for classification tasks. The Crop Recommendation System aims to assist farmers in making informed decisions about crop selection by analysing soil characteristics, climatic data, and geographical parameters [8]. The system allows users to input essential information such as soil nutrient levels (nitrogen, phosphorus, potassium), rainfall patterns, and geographical area. Leveraging a large dataset and employing multiple classification models, our system predicts the most suitable crops for cultivation in a given location. Furthermore, our Crop Recommendation System

provides an innovative feature for crop disease detection using image classification techniques. By allowing users to upload images of leaves of the crop, showing symptoms of disease, the system identifies the likely ailment, enabling timely intervention and management practices. The Crop Recommendation System is complemented by a user-friendly web interface developed using Streamlet, facilitating seamless interaction and accessibility for farmers and agricultural stakeholders. Through this interface, users can effortlessly input data, view recommendations, and receive insights regarding crop health.

This paper is organized as follows: section 2 describes the literature review. Section 3 talks about proposed methodology. Section 4 explain the result analysis. Section 5 concludes the paper along with future scope.

II. LITERATURE SURVEY

The rise of smart farming technologies has completely transformed how we approach agriculture. These innovations offer fresh solutions to boost crop production, make better use of resources, and effectively tackle plant diseases. Let's dive into the core concepts and research behind smart crop recommendation systems and plant disease identification, giving you a thorough rundown of what's happening in this field. This early detection helps farmers intervene quickly, stopping the spread of disease and minimizing crop losses [11]

Machine Learning Algorithms

The integration of machine learning has truly transformed agriculture, offering advanced solutions for crop prediction and management. In this section, we'll delve into the various machine learning algorithms that have been successfully utilized to predict crop yields and determine the most suitable crops for cultivation, thereby enhancing agricultural productivity and sustainability [10].

Decision Trees

Decision trees are a foundational class of machine learning algorithms renowned for their effectiveness in classification and regression tasks [3]. In crop prediction, decision trees are invaluable tools for modelling the relationship between diverse soil and environmental factors and the potential yield of different crops. By partitioning the data into subsets based on input features like soil pH, moisture levels, and temperature, decision trees facilitate easy interpretation and visualization of the decision-making process. This simplicity makes them highly beneficial for farmers and agronomists seeking actionable insights.

Random Forests

Expanding upon the principles of decision trees, random forests employ an ensemble learning approach by combining multiple decision trees. This method enhances predictive accuracy and mitigates overfitting by aggregating the predictions of numerous trees [6]. Random forests excel in handling large datasets with numerous input variables, common in agricultural datasets encompassing various factors influencing crop growth and health. By reducing model variance, random forests yield more robust and reliable predictions, contributing significantly to improved crop yield forecasts

Convolutional Neural Networks (CNN)

Inspired by the structure of the visual cortex in the human brain, Convolutional Neural Networks (CNNs) are a specialized type of neural network designed for processing structured grid data, such as images. In the context of agriculture, CNNs are widely used for plant disease identification. By analysing images of crops, CNNs can learn to detect patterns indicative of various diseases, enabling early and accurate diagnosis. CNNs are especially effective for this task due to their ability to automatically extract relevant features from images, making them well-suited for analysing plant images captured in the field or through remote sensing technologies.

Optimization of Web based Crop Recommendation Systems

In the realm of web-based smart crop recommendation systems, optimizing the

performance and user experience of Fig. 1. System architecture these platforms is paramount for their effective utilization by farmers and agricultural stakeholders. This optimization involves several key strategies. Firstly, ensuring responsive design is crucial to enable seamless access to the application across various devices, including desktop computers, tablets, and smartphones "Fig.1". Additionally, prioritizing fast loading times enhances user engagement and satisfaction, particularly for farmers in remote areas with limited internet connectivity. Lastly, integrating external data sources, such as weather forecasts, enriches the system with comprehensive and up-to-date information to support informed decision-making.

III. PROBLEM STATEMENT

Crop Disease is a significant issue in the Agricultural Production Industry and causes yield losses due to disease, pest, and adverse environment conditions on crops. By detecting crop disease early and accurately, farmers can effectively manage their crops, control unnecessary applications of pesticides, increase productivity and ensure food security. Traditional methods of detecting crop disease rely heavily on the expertise of knowledgeable individuals and the inspection of fields with hands-on field experience, which requires considerable time and expense, and is not easily available for smallholder farmers.

With the growth of digital images and advancements in technology through using machine learning and deep learning, Automatic Disease Detection for Leaf Crop has become a highly capable technology for the agricultural industry. There are many options for Farmers who currently have established systems for predicting crop diseases based on leaf images, yet there is still an opportunity to develop reliable and user-friendly tools for Farmers, which allows them to not only predict disease occurrence from images of crop leaves but also recommend corrective and preventative treatment methods based on their identified disease occurrence.

IV. PROPOSED SYSTEM

The implementation serves as a pivotal factor inside the framework of the Smart Crop Recommendations with Plant Disease Identification. This phase encapsulates the interpretation of theoretical underpinnings and methodologies elucidated in preceding sections into tangible packages [10]. It encompasses the systematic improvement of the system, rigorous execution of trying out protocols, and meticulous analysis of outcomes to check adherence to stipulated necessities. The subsequent subsections provide an exhaustive elucidation of the methodologies embraced, the checking out and verification methodologies deployed, the complete analysis of effects derived, and the first-class guarantee mechanisms enacted to uphold the reliability and efficacy of the gadget [8].

Methodology

Datasets

This dataset consists of 2200 rows in total. Each row has 8 columns representing Nitrogen, Phosphorous, Potassium, Temperature, Humidity, PH, Rainfall and Label NPK(Nitrogen, Phosphorous and Potassium) values represent the NPK values in the soil. Temperature, humidity and rainfall are the average values of the surroundings environment respectively. PH is the PH value present in the soil. The Label column tells us the type of crop that's best suited to grow based on these conditions. Label is the value we will be predicting. Dataset for crop disease identification consists of the secondary dataset encompasses a collection of 70,295 plant snap shots exhibiting a spectrum of illnesses. This dataset amounts to five gigabytes in length, all standardized to a decision of 128x128 pixels. It encompasses a complete of 38 distinct instructions, which includes 14 distinct plant types and 26 identifiable illnesses. Following training, the set of rules demonstrating the highest accuracy became selected for similarly evaluation and application.

Data Preprocessing

Data preprocessing, the procedure of reworking uncooked information right into a format amenable to evaluation by way of analysts and records scientists for the purpose of making use of machine

learning algorithms to derive insights or expect effects, is imperative to statistics education. In Plant disease identification model the raw pictures acquired from the dataset may also incorporate noise, therefore necessitating preprocessing earlier than integration into the mastering module.

Train and Test Split

The technique includes partitioning the dataset into awesome education and trying out subsets using the `train_test_split()` method to be had inside the scikit-examine module. Specifically, inside this framework, the dataset comprising 2200 information factors has been apportioned such that 80% of the dataset, equating to 1760 records factors, is allotted to the training subset, while the closing 20%, amounting to 440 information points, paperwork the trying out subset.

Predicting the model In the context of forecasting the chance of a particular final results, the time period "prediction" denotes the result acquired from an algorithm subsequent to its schooling on a previous dataset and its next software to novel statistics. The prediction of the version is accomplished via the usage of the predict technique, which operates on the test feature dataset. This process yields an output within the form of an array containing the anticipated values [9].

Model evaluation of plant disease to examine the version's performance, the following steps are carried out: • Initially, 80% of the pics from an excellent dataset are allocated for training purposes, at the same time as the ultimate 20% are reserved for validation. • Validation statistics is utilized to assess accuracy by using employing the expect function and exactly extracting features. • Additional photos are captured to affirm detection accuracy once best outcomes are obtained from the validation process

Confusion Matrix and Classification Report The strategies of Confusion Matrix and Classification Report are imported from the metrics module within the scikitlearn library. They are computed via using the actual labels present in the check datasets along the expected values [1]. The Confusion Matrix affords a comprehensive breakdown of the frequency of real

negatives, false negatives, real positives, and false positives within the dataset [1].

Precision denotes the capability of a classifier to correctly pick out the wide variety of fine predictions among the ones which might be deemed fantastic which is shown in "(1)". It is computed because the ratio of real positives to the sum of genuine positives and fake positives for every class [1]. Where the accuracy of Precision-Positive Predictions; True Positive (TP) and False Positive (FP)

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall, in the context of classification, signifies the classifier's ability to correctly identify all high quality times from the confusion matrix which is shown in equation. Mathematically, it's miles computed because the quotient of real positives divided through the sum of proper positives and fake negatives for every magnificence which is shown in "(2)".

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$$\text{Recall} = \frac{TP}{TP + FN}$$

Where recall is the proportion of correctly detected positives; False Negative, or FN

The F1-Score rating represents a weighted harmonic suggest of precision and don't forget, in which a price of zero. 0 denotes the poorest overall performance, at the same time as 1.0 signifies most efficient performance. As precision and do not forget are imperative additives in its calculation, F1 ratings commonly yield lower values as compared to accuracy measurements which is shown in "(3)".

$$F1 - \text{Score} = \frac{2 * PR}{(P+R)}$$

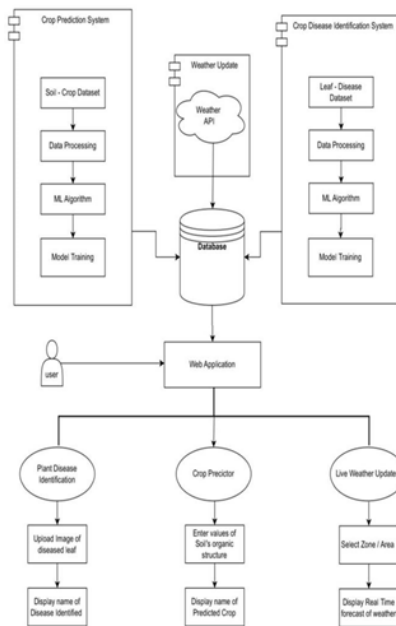
Where P-Precision; R-Recall

Accuracy Model accuracy, a metric indicating the proportion of correct predictions relative to the full number of predictions made, is a fundamental aspect of model assessment. It is computed the use of the `accuracy_score()` technique available in the scikit-examine metrics module which is shown in "(4)".

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Where TP-True Positive; FP-False Positive; TN-True Negative; FN-False Negative

Flow Diagram



Real Time Operational Application

The real-time operational application provides immediate assistance to farmers and agricultural entities by leveraging machine-learning algorithms and image processing technology to detect and respond to crop diseases in real-time. By detecting diseases early, the application reduces crop loss and increases the efficiency of agriculture production.

System Functionality

The application operates by capturing images of the crop leaves in real-time with mobile devices or cameras. Those images are analysed using a trained deep-learning model to identify and categorize crop diseases and their associated treatments. Upon identification of the disease, crop farmers and other agricultural professionals receive intelligent recommendations regarding prevention and remediation through products such as pesticides and fertilizers, and viable farming methods.

Leaf Disease Prediction Using CNNs

Leaf disease prediction uses a type of deep-learning neural network known as a convolutional neural network (CNN). CNNs have been used extensively to classify images. The CNN model will be trained on a collection of images that represent healthy and diseased leaves from a variety of crops for effective prediction.

Processing Steps:

Capturing the image

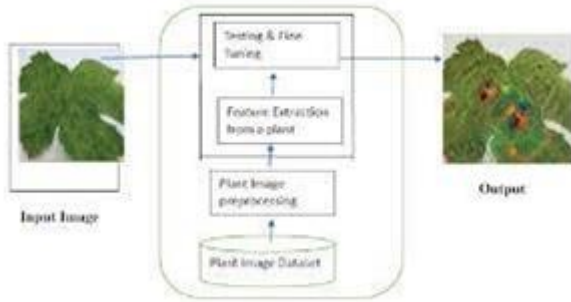
Pre-processing the image by resizing, normalizing, removing noise, etc.

Extracting features from the image with a CNN Identifying and classifying the disease (e.g., bacterial, fungal, viral, or healthy) Producing a confidence score Predicting in real-time allows farmers to take immediate preventative measures against disease spreading.

Crop Disease Recommendations

After identifying the disease, the system generates intelligent recommendations based on the particulars of that disease and what options exist to mitigate its effects.

Architecture Diagram



The Backend Server/Cloud Platform is used to host the ML model, respond to API requests, and store and process all user uploaded images and predictions.

Finally, the Output Module displays the name of the disease and confidence score, along with treatment recommendations for the user. Below is a textual

The system architecture we designed enables real-time detection of diseases on leaves, as well as recommendations for crops based on diseased leaves. It is designed in a client-server configuration that is integrated with both a deep learning model and a recommendation engine.

The user interface is the mobile application or web interface through which the user (farmer) can take images of leaves using the device's camera, and view predictions of diseases, and suggested solutions.

The Image Acquisition Module allows the user to upload real-time images of leaves to the system and provides for the proper format and resolution for those images.

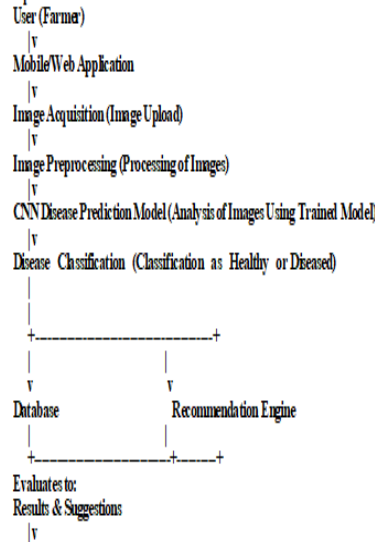
The Image Preprocessing Module processes the user-uploaded images by resizing, removing noise, normalizing, and enhancing the images.

The Disease Prediction Model uses a Convolutional Neural Network (CNN), which has been trained to take the uploaded leaf images, extract features from them, and then classify them as either healthy or diseased, as well as identify which type of disease is present.

The Database stores all images of crops along with their respective disease labels, treatments and recommendations, and all previous predictions made by the system.

The Recommendation Engine matches the disease prediction with the appropriate treatment or recommendation, and provides additional information such as preventive measures, types of pesticides and fertilizers, etc.

representation of the workflow for the aforementioned architecture.



Results

Seven classification algorithms have been selected, and their respective accuracies have been assessed. For the second task, the preeminent photograph classification convolutional neural network (CNN) architectures were skilled. The ensuing tables gift the corresponding outcomes.

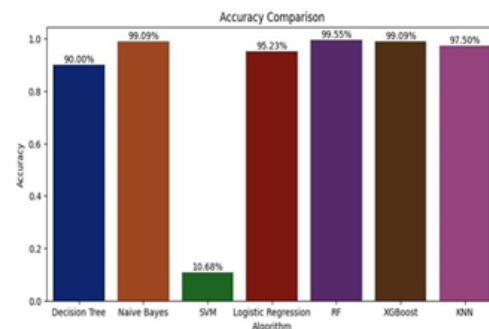


Fig. 2. Accuracy comparison

Table.1 offers the accuracy of crop advice responsibilities across diverse algorithms [4]. This desk unequivocally demonstrates that the random

wooded area set of rules surpasses all others, accomplishing an extraordinary accuracy of 99.54%.

Table I. Accuracy Vs Algorithms

Algorithm	Accuracy
Decision Tree	90.0
Gaussian Naive Bayes	99.09
Support Vector Machine (SVM)	10.68
Logistic Regression	95.23
Random Forest	99.55
XGBoost	99.09
KNN	97.50

"Fig.3" show that Random Forest models consistently perform well across different crops, often outperforming other models. While some models excel with specific crops, they show varying accuracy overall. Random Forest stands out for its stability and versatility, making it a reliable choice for a wide range of crops. This highlights the model's effectiveness in providing consistent accuracy compared to the more specialized performance of other models

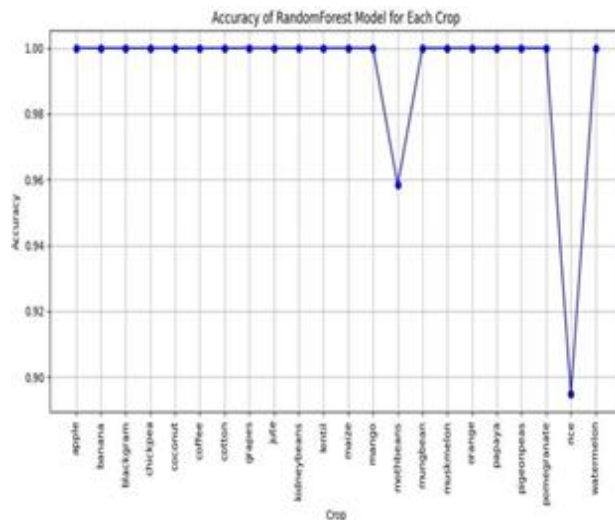


Fig. 3. Accuracy vs Crop graph for random forest model

In this study, we employed a convolutional neural network to detect plant diseases from a dataset containing images of various plant species. The dataset, consisting of 17,572 images across 38 distinct classes, was organized into a validation set using the `tf.keras.utils.image_dataset_from_directory` function, ensuring that each image was resized to 128x128

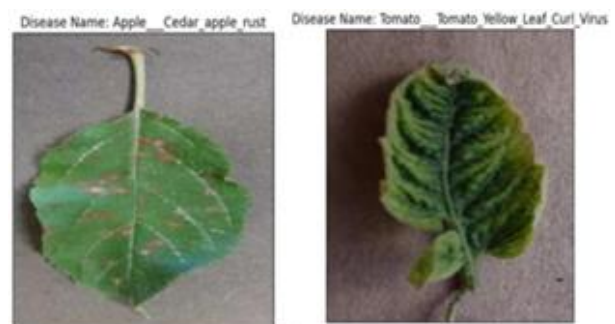
pixels to match the input requirements of our model. The class names, representing various plant diseases and healthy conditions, were automatically inferred from the directory structure. We utilized a pre-trained CNN model, which was loaded from a saved.keras file, to perform the predictions [5]. Here we use dropout layer to prevent overfitting by randomly setting a fraction of input unit to zero at each updated during training.

For visualization and testing purposes, a sample image of a potato plant affected by early blight was processed. This image was read, converted from BGR to RGB using OpenCV, and resized to the required dimensions. The preprocessed image was then fed into the model to obtain predictions.

The model's output was a probability distribution across all classes, from which the class with the highest probability was identified using the `np.argmax` function. The predicted class label, in this case, was displayed alongside the original image, confirming the model's ability to accurately identify the plant disease.

This approach demonstrates the efficacy of CNNs in the automated detection of plant diseases, which can significantly aid in early diagnosis and management, ultimately contributing to better agricultural practices. "Fig.4" illustrates an example of a diseased plant image used for plant disease identification.

The detailed features in the image, such as spots, discoloration, and other symptoms, enable the models to learn and identify various plant diseases, contributing to smarter crop management and healthier yields



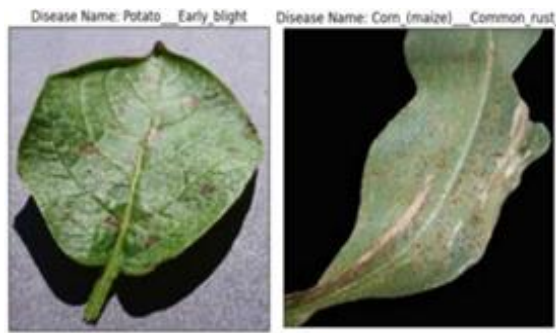


Fig. 4. Example of diseased image

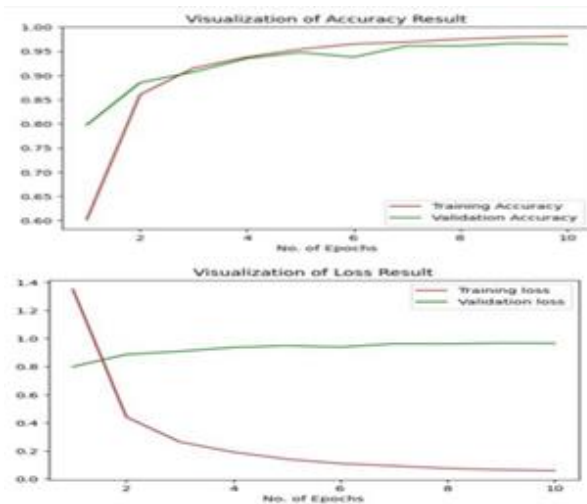


Fig. 5. Training and Validation (accuracy and loss) simple CNN

V. CONCLUSION AND FUTURE SCOPE

In conclusion, the project has successfully developed a sophisticated system for smart crop recommendation and disease detection using advanced technologies and techniques. By combining machine learning algorithms, and real-time data processing, the project provides insights that can be applied to improving crop management and reducing the impact of plant diseases. Modular and scalable design patterns adopted while adhering to industry standards ensured the reliability, scalability and maintainability of the solution. Using best practices of database design and user-centric interface design principles, provided project's farmers regardless of their technical skills. facilitated seamless communication and usability. Overall,

precision agriculture has improved dramatically through integration of strategies, innovation and adherence to industry standards. Integration of cutting-edge technologies for smart crops recommendations and disease detection have provided farmers with the necessary tools for informed decision making and sustainable agricultural practices.

In future, the dataset can be frequently updated with new samples and cases. The Performance of Crop Recommendation and Plant Disease Identification, implemented by Machine learning classification and prediction models can be improved by integrating it with practices, such as Multispectral and Hyperspectral imaging data for insights on plant's health and Reinforced Learning to optimize the performance of existing strategies. Including the Temperature and rainfall data of the region in which the farm is can also help in suggesting best suited crop for them, potentially reducing crop losses and improving yields.

More features like Profit oriented Crop prediction for the farmers based on the selling price of the crops and investment needed for that crop can be added. We can also include Crop Growth Schedule managers in getting the new farmer acquainted with timeline of different process in farming and to help in watering, fertilizing and pest cleaning timely and regularly. The concepts of edge computing can also be implemented. By integrating the system with a moveable device with camera and sensors can also help the farmers in real time monitoring of their farms. Furthermore, development of a collaborative platform, inviting various farmers, researchers and agronomists to share data and insights on various cases and info about any new ones will also have a significant impact as such Crowd-sourced data collection could also help in significantly improving model accuracy.

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