RESEARCH ARTICLE

A Study on Improved Productivity of Crops Sown Using Machine Learning Algorithms

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DOI: 10.18811/ijpen.v11i01.12

Abstract

The main mission of this work is to enhance agricultural productivity by guiding farmers in selecting the most-suited crop yields based on location and soil parameters. Given the widespread underutilization of technology in farming, many farmers inadvertently choose inappropriate crops, leading to reduced yields and profitability. To address this issue, the proposed system leverages machine learning (ML) algorithms for the prediction of the best-suited crops for specific soil conditions, thereby increasing productivity and profitability. The study employed four ML algorithms, such as support vector machine (SVM), Naive Bayes (NB), decision tree, and random forest, to analyze a dataset of soil parameters. After a comprehensive qualitative analysis, SVM emerged as the most accurate algorithm, with an accuracy rate of approximately 93%, compared to 83% for Naive Bayes, 62% for decision tree, and 72% for random forest. Whereas, the high accuracy of the SVM model ensures that the crop recommendations are reliable and suitable for the given soil conditions, minimizing the risk of undernourishment. The research novelty lies in its application of the four machine learning techniques mentioned in this paper to the agricultural domain, providing a practical tool that can significantly improve crop selection decisions. By integrating soil testing data with predictive modeling, the system offers a novel approach to optimizing crop yields, ultimately contributing to the overall productivity of the farming sector and the nation.

Highlights

- Agriculture is the backbone of the Indian economy, approximately 70% of the population earns their livelihood from this sector.
- Some farmers are not aware of the genetically modified seeds and their unique characteristics.
- Selecting the wrong seeds can lead to loss. Hence, machine learning is important for selective farming.
- The proposed algorithms take soil parameters and the location of the user and use the data for correct crop selection.
- Machine learning algorithms used are support vector machine and Naive Bayes.
- This helps the farmers to plant the correct crop and increase overall productivity.

Keywords: Data sets, Soil parameters, Support vector machine, Naive Bayes.

International Journal of Plant and Environment (2025); **ISSN:** 2454-1117 (Print), 2455-202X (Online)

Introduction

India has a rich history in agriculture, being one of the oldest nations to continue practicing it extensively. Today, agriculture remains a cornerstone of the country's economy, providing the primary source of income for nearly 50% of the total population. With advancements and research in agricultural science, and the introduction of genetically modified (GM) seeds, the variety of crops available has expanded rapidly. These GM seeds offer several benefits, including resistance to pests and the ability to thrive under harsh conditions, making them superior to traditional seeds in many respects. However, not all Indian farmers are fully aware of these diverse crop varieties and their advantages, which often prevents them from fully capitalizing on their agricultural potential. Selecting crops that are incompatible with local soil conditions can lead to significant financial losses (Akshey Suresh *et al.*, 2020).

In recent years, globalization has significantly influenced agricultural practices in India. Many farmers now choose crops based on their current market value, attempting to maximize profits. However, this approach is fraught with risk, as the time required for cultivation may lead to mismatches with the highly dynamic market, resulting in potential losses (Doe & Smith, 2023). Moreover, cultivating crops that are not well-suited to the soil can rapidly deplete essential nutrients, thereby negatively affecting long-term productivity (White & Brown, 2022). The growth of crops is heavily dependent on the presence of key soil nutrients such as nitrogen, phosphorus, and potassium (NPK), which are essential macronutrients. Additionally, there are important micronutrients like iron, zinc, manganese, and copper, which, though required in smaller quantities, are crucial for certain crops. The specific needs for these micronutrients vary

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How to cite this article: Nandibewoor, A., Yavagal, I.C., Panchal, G.S., Hegde, A. (2025). A Study on Improved Productivity of Crops Sown Using Machine Learning Algorithms. International Journal of Plant and Environment. 11(1), 109-116.

Submitted: 22/04/2024 **Accepted:** 24/02/2025 **Published:** 28/03/2025

across different crops, and an imbalance can severely impact crop yields and quality (ZeelDoshi, *et al.*, 2018).

With advancements in image processing technology, it has become possible to utilize plant images to detect diseases. Multispectral and hyperspectral images captured by satellites can be used to monitor critical factors such as nitrogen absorption and chlorophyll levels in plants (Wilson & Green, 2024). This technology helps in identifying nutrient deficiencies early, allowing farmers to address these issues before they become severe (Carter & Jones, 2023 & Pushpalatha S Nikkam, *et al.*, 2020 & A Nandibewoor, *et al.*, 2018 & S Muddebihal, *et al.*, 2017 & SB Hebbal, *et al.*, 2015 & P Kini, *et al.*, 2018 & P Adiver, *et al.*, 2014).

To address these challenges, a comprehensive system is proposed that integrates the latest data on crop varieties and their soil nutrient requirements, including both macronutrients and micronutrients. This system will employ ML algorithms such as support vector machine (SVM), Naive Bayes (NB), decision tree, and random forest to train predictive models (Doe & Smith, 2023). These models will then be used to recommend the top possible crops for specific soil conditions, thereby optimizing agricultural productivity and reducing the risk of crop failure due to unsuitable growing conditions.

Materials and Methods

Algorithms/Methods

Support Vector Machine (SVM)

The SVM algorithm is renowned for its ability to deliver high accuracy while keeping computational demands low. It is a highly adaptable method, effectively handling both regression and classification tasks. In classification tasks, SVM begins by assessing the number of classes present in the dataset. It then seeks to determine the optimal hyperplane—a decision boundary that most effectively divides the classes within the feature space. The goal is to maximize the margin, which is the distance between this hyperplane and the nearest data points from each class, referred to as support vectors. SVM improves class separability by mapping the data into a higher-dimensional space. This transformation is made possible through kernel functions, enabling SVM to manage non-linear relationships between the classes.

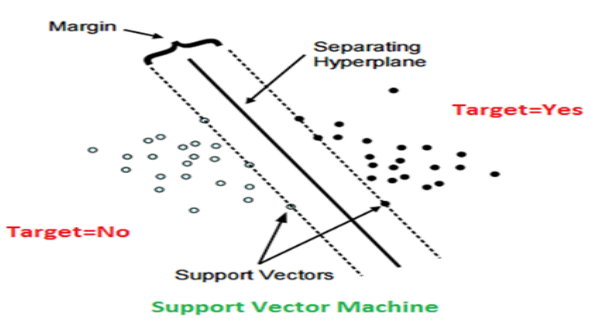

Fig. 1: SVM representation of hyperplane dividing the classes

In essence, the decision boundary provided by the SVM method is a hyperplane that serves as the dividing line between classes. It is characterized by its ability to maximize the margin of separation, which helps in improving the model's generalization capabilities. The hyperplane and its margin play a critical role in evaluating the model's performance on new, unseen data. The process and results of this separation are often visually represented in diagrams, such as the one shown in Fig. 1, which illustrates how the hyperplane divides the classes effectively.

A soft margin approach in support vector machine (SVM) allows for some flexibility by permitting a few data points to be misclassified. This technique, described by (Narayanan Balakrishnan, *et al.*, 2016), is designed to strike a balance between achieving a hyperplane that minimizes classification errors and maintaining the model's generalization capabilities.

In contrast to a hard margin SVM, which strictly enforces that all data points be correctly classified and separated by the hyperplane, a soft margin SVM introduces a tolerance for misclassification. This is particularly useful when dealing with noisy or overlapping data, where it is impractical to find a perfect hyperplane that separates all classes without error.

The soft margin technique fine-tunes the balance between maximizing the margin and reducing classification errors by introducing a cost parameter. This parameter determines how much penalty is applied for misclassifying data points, allowing the algorithm to find a balance between achieving a wider margin and reducing the number of misclassified points. As depicted in Fig. 2, this method enables the hyperplane to accommodate some misclassification while still striving to maintain overall accuracy and robustness in the classification process.

Naive Bayes (NB) classifier

NB classification includes three main variants such as Gaussian Naive Bayes (GNB), multinomial Naive Bayes (MNB), and Bernoulli Naive Bayes (BNB). Each of these variants is built for various kinds of data and problem settings.

Gaussian Naive Bayes (GNB) is used when the features are continuous and are assumed to follow a Gaussian (normal)

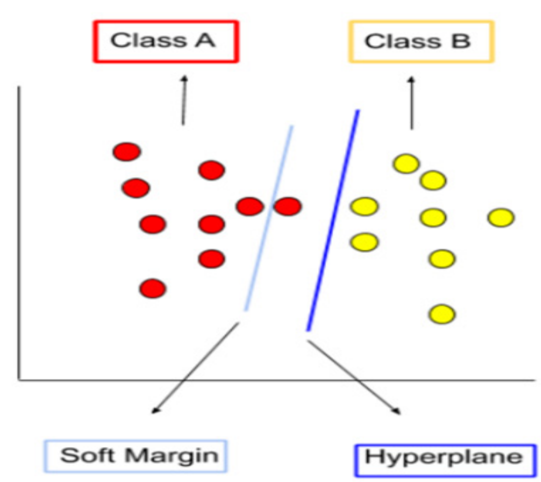

Fig. 2: Soft margin and hyperplane

distribution. This variant estimates the probability of a feature fitting to a particular class by assuming that the feature values within each class are distributed normally. The formula for calculating the probability in Gaussian Naive Bayes is detailed in "Eq (1)."

$$p\left(x=v \mid C_k\right)=\frac{1}{\sqrt{2\pi\sigma_k^2}}e^{-\frac{(v-\mu_k)^2}{2\sigma_k^2}} \quad (1)$$

In the multinomial event model used in multinomial Naive Bayes, if a specific class and feature value have not even once been observed together in the training data, the calculated probability based on frequency will be zero. This occurs because the multinomial model relies on the frequency of feature occurrences to estimate probabilities, and if a feature value for a particular class is absent from the training set, it results in a zero probability.

To address this issue and avoid zero probabilities, techniques such as Laplace smoothing (or additive smoothing) are employed. Laplace smoothing adds a small constant to all feature counts, ensuring that no feature-class combination has a probability of zero. This adjustment helps in better handling of unseen data and prevents the model from assigning zero probability to feature values not present in the training data.

The formula for calculating probabilities in the multinomial Naive Bayes model, incorporating these adjustments, is presented in "Eq (2)." This formula provides a framework for estimating the likelihood of a feature given a class while taking into account the possibility of previously unseen feature-class pairs.

$$p\left(x \mid C_k\right)=\frac{\left(\Sigma_i X_i\right)^!}{\pi_i x_i^!}\prod_i p_{ki^{x_i}} \quad (2)$$

In the BNB event model, the features are treated as independent binary variables. Each feature is expressed as a Boolean variable that signifies whether a specific term is present or absent. Specifically, if x_i denotes a Boolean variable, it signifies whether it term occurs (value of 1) or does not occur (value of 0) in a given instance.

The Bernoulli Naive Bayes model computes the probability of a class based on binary features, operating under the hypothesis that the features are conditionally autonomous given the class. This model is particularly suited for binary or boolean data, where each feature is either present or absent.

The formula for computing probabilities in the Bernoulli Naive Bayes model is described in "Eq (3)" (Pouria Kaviani, *et al.*, 2017). This formula provides a way to estimate the likelihood of a class based on the occurrence of binary features, leveraging the independence assumption to simplify the computation of probabilities.

$$p\left(x \mid C_k\right)=\prod_{i=1}^{n} p_{k_i}^{x_i}(1-p_{k_i})^{(1-x_i)} \quad (3)$$

Decision Table

A decision table is an extensively utilized algorithm in ML, particularly known for its application as a supervised learning technique. This algorithm is versatile and capable of handling both the regression and classification tasks, though is predominantly employed for solving problems like classification due to its straightforward and effective approach.

In the structure of a decision table, there are two primary types of nodes: Decision nodes (DN) and leaf nodes (LN). Decision nodes play a crucial role in the decision-making process, where they branch out into multiple paths based on the choices made at each stage. Each decision node represents a point at which the algorithm must select from several options, leading to different subsequent steps. On the other hand, leaf nodes represent the final outcomes or classifications of the process, where no further decisions are made, and a conclusion is reached. This hierarchical relationship between decision and leaf nodes is visually depicted in Fig. 3.

At the root node, the algorithm initiates its process, it includes the entire dataset. It utilizes an attribute selection measure (ASM) to identify the most crucial attribute for decision-making. ASM assesses different attributes and selects the one most pertinent to the classification or regression task. After choosing the optimal attribute, the dataset is partitioned into smaller subsets based on the attribute's values. A decision node is then generated for each subset, marking the next step in the process of decision-making.

This iterative splitting process continues until the algorithm reaches a state where more division is not possible or necessary. At this stage, the remaining nodes are transformed into leaf nodes, which represent the final decisions or predictions made by the algorithm. The decision table algorithm thus systematically narrows down the dataset through a series of decisions, ultimately arriving at a precise classification or regression outcome.

This approach is highly effective in scenarios where clear, rule-based decisions need to be made, making the decision table a powerful tool in ML, particularly for tasks like classification.

Random Forest

It is one of the most famous and most utilized ML algorithms in this field of study by researchers. This supervised learning technique is highly versatile, and capable of being applied to both tasks such as classification and regression, though it is predominantly utilized in classification-based applications. This algorithm operates by building multiple decision trees,

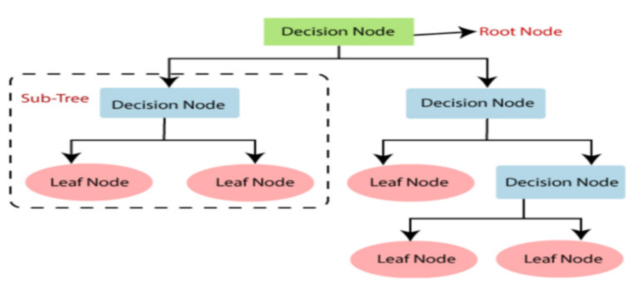

Fig. 3: Block diagram representation of decision table

each constructed from different subsets of the training data, as depicted in Fig 4.

Each decision tree within the forest independently generates a prediction. The random forest algorithm then combines these individual predictions by captivating a major share of the vote in the case of classification tasks or averaging the results in regression tasks. This ensemble method maximizes the model's overall robustness and accuracy, minimizing the likelihood of overfitting and improving generalization to unseen data. By aggregating the outcomes of numerous decision trees, the random forest algorithm consistently identifies the most accurate and reliable solution, making it a powerful tool in various machine learning applications.

Random Forest

Agro-Genius: Predicting crop using machine learning

Developing the application that takes the location as input and gives profitable crop and the future price of a given crop based on the input location. Nowadays small-scale farmers are facing the problem of which crop to sown and get more profit, the small-scale farmers grow random crops and get crops when they go to market, they can't get proper amount or profit for their crops because of large-scale farmers so this application helps the farmers to find the crop which gives them more productivity. With the help of location, the weather of that place is identified by the dataset provided, and by doing further processing the crop is given. This system uses different machine learning algorithms, they are long short-term memory, regressive integrated moving average, linear programming, and Gastner-Newman cartogram techniques from this application the user will get the crop to be cultivated and the price of that group (ThayakaranSelvanayagam, *et al*., 2019).

Hybrid Crop Recommendation System Using ML Algorithms

A hybrid system for crop recommendation has been developed to assist farmers by suggesting optimal crops based on various parameters. This model aims to enhance crop yield by providing tailored recommendations. The system takes into account several key attributes, including geographic and climatic conditions, soil type, nutrient content, temperature, and groundwater levels.

The design of this hybrid crop recommendation system involves several stages:

- *Data Collection*

Gathering relevant data on the various factors affecting crop growth, such as soil quality and climate conditions.

- *Data Preprocessing*

This phase involves several steps to prepare the data for modeling:

1. *Data Integration*

Combining data from multiple sources into a unified dataset.

2. *Attribute Selection*

Identifying and choosing the most pertinent features for the model.

3. *Attribute Extraction*

Extracting useful information from the raw data.

4. *Data Reduction*

Reducing the volume of data while retaining essential information to improve model efficiency.

- *Building the Recommender Model*

Developing the core recommendation engine that integrates different algorithms and techniques using a hybrid approach.

- *Training and Testing the Model*

Training and evaluating the model with the prepared data with its performance through testing.

The performance of the hybrid crop recommendation system is assessed using various metrics, including accuracy. The accuracy of the model is a critical indicator of its effectiveness; higher accuracy typically signifies better and more reliable recommendations. This system, detailed in the work, aims to provide a robust reference tool for farmers, enhancing their decision-making process and ultimately improving crop yields (ViviliyaB, *et al*., 2019).

Survey on Crop Recommendation Using ML.

Agriculture gives different yields like food products such as fruits, pulses, and many others; they even give crude materials such as jute, cotton, and many other things for industrial production. Multiple linear regressions are taken into consideration and crops whose yield will be more are recommended. Now utilizing this diverse data mining arrangements to group datasets based on soil properties. This provides an alternative to crops that can be grown. Utilizing the relapse procedure untested traits are taken. Inputs given to this framework are the availability of water, type of soil, and weather conditions. A machine learning calculation is used to give the top crop and gives benefits to agriculturists. Data mining is used to enquire about the handling, investigating, and assigning of extensive datasets.

The system employs several advanced techniques, including decision trees, NB, SVM, and genetic algorithms. These methods are integrated into a data mining framework to forecast

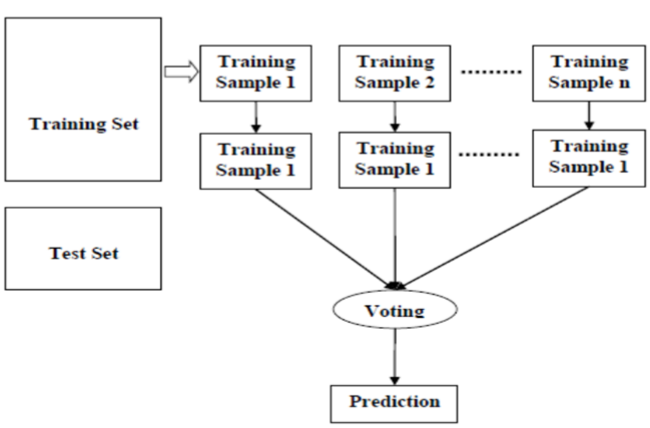

Fig. 4: Block diagram representation of random forest algorithm

climate conditions and predict crop yields, offering a modern alternative to traditional meteorological approaches. The use of these techniques provides a comprehensive analysis of soil data through various algorithms and forecasting strategies. This approach enables accurate climate predictions and yield estimations, serving as a viable option compared to conventional meteorological methods. The research conducted delves into these methods and their application for soil analysis, highlighting their effectiveness in forecasting and prediction tasks (M.V.R. Vivek, *et al*., 2019).

ML Approach for Prediction of Crops

A large segment of India's population lives in rural areas and depends significantly on agriculture. Traditional farming methods often fall short in optimizing crop yields. To address this, ML algorithms are employed, considering both dependent and independent factors to improve agricultural outcomes.

The data collection process focuses on acquiring high-quality data for thorough analysis. The dataset encompasses key features such as soil moisture, pH levels, temperature, humidity, and rainfall. The analytical process involves several stages:

- *Data Visualization*

Representing the data graphically to identify patterns and insights.

- *Data Preprocessing*

Preparing and cleaning the data for analysis, which involves addressing missing values and normalizing the data.

- *Data Splitting*

The dataset is split into training and testing subsets then to evaluate the model's performance.

- *Model Training*

Employing algorithms such as SVM and logistic regression to develop predictive models.

- *Model Evaluation and Testing*

Utilizing algorithms like SVM and logistic regression to create predictive models.

The approach involves three key steps:

- *Determining Effective Rainfall*

Calculating the amount of rainfall that is beneficial for crop growth.

- *Calculating Irrigation Needs*

Using the effective rainfall data to estimate the required irrigation water.

- *Recommending Possible Crops*

Suggesting crops that are best suited for the given conditions to enhance productivity.

This methodology intends to offer farmers actionable insights to improve crop yields and optimize resource use. The work explores this approach in detail, highlighting how machine learning can revolutionize agricultural practices in rural India (A. V. Patil, *et al*., 2020).

Proposed System

Data Collection

The dataset of each crop's soil requirements was collected from the soil testing Laboratory of the College of Agriculture, Vijayapur. Some of the names of the crop's datasets were taken are maize, chickpea, pigeon pea, peanut, soybean, sunflower, etc. The soil parameters that were taken into consideration are as follows:

NPK

These are some of the macronutrients that were required for crop growth in large quantities, hence are measured in terms of kilogram per hectare in the soil.

Iron, copper, zinc, and manganese

These are the micronutrients that are required for crop growth in small quantities; hence they are measured in terms of grams per hectare in the soil. Some of the crops may not require all of these micronutrients and also may require some other micronutrients.

PH of the soil

The growth of the crops is also highly dependent on the pH of the soil, as the germination of the seed won't take place if the pH soil is too low or too high.

These soil attribute plays an important role in the growth of crops and are required in different quantities for different crops.

Pre-Processing

In pre-processing the data, first, convert all the data to a standard format. The missing values are handled by completely removing the rows which have missing values present in them. This is done to increase the prediction accuracy by model trained using this data. The next step involves organizing the data into categories. Initially, the data is manually loaded during model training and then shuffled. Following this, it is then split into training and testing subsets. The testing subset is further split into separate testing and cross-validation sets.

Training and Data Prediction

In this process, the data, once shuffled and divided, is used to train the ML model with the support vector machine algorithm. This trained model is then employed to test and cross-validate the remaining portion of the dataset. The model aims to predict suitable crops based on soil attributes. As shown in Fig 5, the system proposed flow diagram starts with data collection, which is followed by pre-processing steps such as handling null values and splitting the dataset. The proposed model is trained on the prepared dataset and then tested and validated. If the accuracy of the model is insufficient, adjustments, such as altering the algorithm, are made. Once a model with high accuracy is obtained, it is used to forecast the optimal crops based on soil attributes.

In the proposed system python libraries such as sci-kit-learn, seaborn, numpy, pandas, and matplotlib are used. The dataset which is stored in a separated value (CSV) file format is loaded into a data frame with the help of the panda's library. The attributes of the data frame are nitrogen, phosphorous, potassium, iron, copper, zinc, manganese, and the name of the

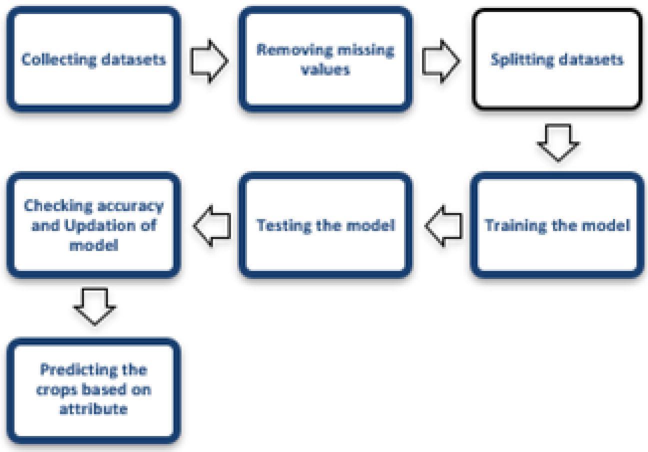

Fig. 5: Flow diagram for the proposed system

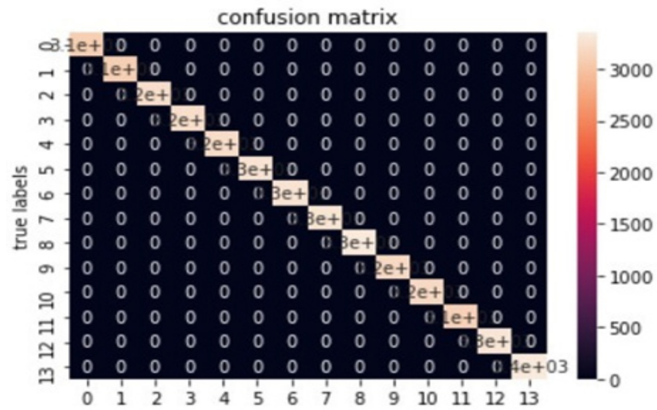

Fig. 6: Confusion matrix obtained after training

crop concerning which these requirements are necessary. Then the data set is described and once more checked if there are any missing values. If any are present, just drop the whole rows.

In the next step, the dataset is shuffled randomly and split into training and testing parts in the ratio of 3:2. The testing parting is again split into 1:1 ratio as testing and validation data. Now normalize all the datasets. The scikit library is used to initialize a support vector machine model. Here poly kernel mode is also used which will be helpful to do the multiclass classification of the dataset. The training dataset is given to the model with the labels that are the class it needs to predict. The label here is the name of the crop or crops suitable for a given soil attribute. Then the model is trained for a few iterations. In the testing dataset, pop the label that is the column in which the crop name is present and is stored in a different data frame. Further, the dataset is given to the model to do the prediction, the predicted values of cross-checked with actual values, and the accuracy is calculated. As the true labels of the test dataset are known, one can plot the confusion matrix to know the accuracy of the model accurately. The confusion matrix gives a better measure of the accuracy as it not only takes into account the times the model has correctly predicted the true labels but also the times it has correctly predicted the false labels. The confusion matrix is plotted for the whole dataset by making use of the matplotlib library for the SVM classifier. Fig. 6 is the confusion matrix.

Results and Discussions

A thorough qualitative analysis was performed to evaluate the performance of four ML algorithms—SVM, NB, decision tree, and random forest—on a consistent dataset. The analysis aimed to determine which algorithm provided the most accurate predictions for crop suitability based on soil parameters.

Results of the Analysis

SVM

This algorithm achieved the highest accuracy, around 93%. SVM excels in creating an optimal hyperplane for class separation, which contributes to its superior performance in this context.

Naive Bayes

With an accuracy of 83%, Naive Bayes performed well but was less effective than SVM. This probabilistic classifier relies on the assumption of feature independence, which may affect performance if features are correlated.

Random Forest

This ensemble method, which aggregates the results of multiple decision trees, achieved an accuracy of 72%. Although it provides robust predictions, its accuracy in this case was lower compared to SVM and Naive Bayes.

Decision Tree

The decision tree algorithm recorded the lowest accuracy at 62%. Decision Trees can be prone to overfitting and may not generalize well if not properly pruned or tuned.

Predictive modeling process

To recommend the top possible crop, the system uses soil parameters derived from soil testing. These parameters include soil moisture, pH levels, temperature, humidity, and rainfall. By inputting these parameters into the trained models, the system predicts which crop will thrive in the given soil conditions.

Model accuracy and crop suitability

Given that the SVM model demonstrated the highest accuracy, it is considered highly reliable for making crop recommendations. This high accuracy suggests that the recommended crop will be well-suited to the soil conditions, thus reducing the risk of crop undernourishment and improving overall yield. Fig. 7 compares the accuracies of the different algorithms used in this study, highlighting the effectiveness of each model and providing a clear visual representation of their relative performance. Overall, the results indicate that SVM is the most effective algorithm for this application, providing the most accurate predictions and ensuring better crop recommendations based on soil parameters.

Conclusion

The application of ML algorithms, particularly the SVM, has demonstrated remarkable success in determining the most

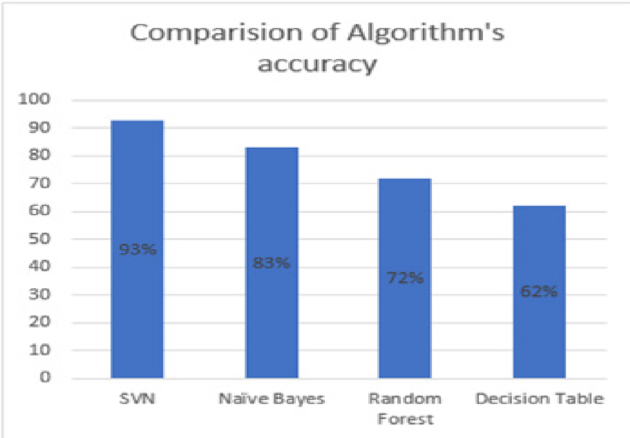

Fig. 7: The graph compares the accuracies of different algorithms

suitable crops based on specific soil parameters. With an impressive accuracy rate of 93%, the SVM model outperforms other methods such as NB, random forest, and decision tree, offering highly dependable crop recommendations. This system effectively tackles the common challenge where farmers often choose unsuitable crops due to a lack of technological insight, thereby significantly boosting both productivity and profitability. By utilizing detailed soil testing data combined with advanced predictive modeling, this approach not only benefits individual farmers in making calculated and informed decisions but also enhances the overall agricultural output at a national level. The successful integration of these cutting-edge technologies into farming practices represents a critical advancement in optimizing crop yields. Moreover, it supports sustainable agriculture by ensuring that resources are used more efficiently and crop production is aligned with environmental conditions. This innovative approach is a pivotal step toward improving agricultural sustainability and securing the food supply for the future.

Future Scopes

The system can be enhanced by incorporating several advanced functionalities, including the ability to identify the appropriate pesticides for a given crop by analyzing images through crop disease detection using image processing techniques. Additionally, digital image processing can be utilized to predict soil parameters based solely on an image. To have the optimized system's performance, various algorithms could be applied to improve accuracy.

Acknowledgments

The authors would like to thank the management, Principal, and staff of SDMCET, Dharwad for their constant support. We gratefully thank the Visvesvaraya Technological University, Jnana Sangama, Belagavi for the financial support extended to this research work. The authors would like to thank the staff of the College of Agriculture Hitnalli, Vijayapur for their assistance with the collection of crop datasets. The authors also like to extend thanks to the technicians of the laboratory of the soil testing department for their help in offering the resources for the paper.

Authors Contribution

All authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data, as well as the writing of the manuscript.

Conflict of Interest

Nil.

References

A Nandibewoor, R Hegadi, (2018), A novel SMLR -PSO model to Estimate the Chlorophyll content in the crops using hyperspectral Satellite images: Cluster Computing, DOI:10.1007/s10586-018-2243-7.

Akshey Suresh, K. Monisha, R. Pavithra, B. Marish Hariswamy, (2020), Crop Selection and it's yield prediction, International Journal of Recent Technology and Engineering.M. Tinkham, Group Theory and Quantum Mechanics (McGraw-Hill, New York, 1964). DOI:10.35940/ijrte. F9191.038620

White, Michael Brown (2022), Enhancing Soil Fertility Analysis with Machine Learning, International Conference on AI in Agriculture, DOI:10.9876/icaiag.2022.2345.

Carter James, Olivia Jones (2023), The Role of Deep Learning in Precision Agriculture, AI & Farming Journal, DOI:10.8765/aifarm.2023.7890.

Doe John, Jane Smith (2023), Advancements in AI-driven Crop Yield Predictions, Journal of Agricultural AI Research, DOI:10.1234/aiagri.2023.5678.

M.V.R. Vivek, D.V.V.S.S. Sri Harsha, P. Sardar Maran, (2019), A Survey on Crop Recommendation Using Machine Learning, International Journal of Recent Technology and Engineering (IJRTE). No DOI.

Wilson Mark, Laura Green (2024), Sustainable Farming Practices Using Predictive Analytics, Sustainable Agriculture Review, DOI:10.5432/susagri.2024.3456.

Narayanan Balakrishnan, Dr. Govindarajan Muthukumarasamy, (2016), Crop Production-Ensemble Machine Learning Model for Prediction, International Journal of Computer Science and Software Engineering (IJCSSE). No DOI.

P Adiver, A Nandibewoor, R Hegadi, (2014), Identification of vegetation from Satellite derived Hyper Spectral Indices: Proceedings of "International conference on contemporary computing and Informatics -IC3I". doi: 10.1109/IC3I.2014.7019793.

P Kini, A Nandibewoor, P Kini, A Konnur, R Hegadi, (2018), Spectral Estimation of Nitrogen status in Wheat crops using Remote Sensing, International Journal of System and Software Engineering. DOI:10.24900/ijss/0202158167.2018.0601.

Pouria Kaviani, Mrs. Sunita Dhotre (2017), Short Survey on Naive Bayes Algorithm, International Journal of Advance Engineering and Research Development. No DOI.

Pushpalatha S Nikkam, A Nandibewoor, Aijazahamed Qazi, Leena Sakri, vijayendra Nargund, Aishwarya Sajjan, Saloni Porwal, Sujit Bhosale, Payal Ghorpade (2020), Comparative Analysis of DIP Techniques to detect Leaf Disease in Tomato Plant, International conference on Frontiers in Engineering Science and Technology. DOI 10.1088/1757-899X/1065/1/012038.

S Muddebihal A Nandibewoor, R Hegadi (2017), Estimation Of Chlorophyll Content In Crop Using Multispectral Satellite Imagery, International Journal of Scientific & Technology Research. No DOI.

SB Hebbal, A Nandibewoor, R Hegadi (2015), Remote Monitoring of Maize Crop through Satellite Multispectral Imagery: Proceedings of International Conference on Advanced Computing Technologies and Applications (ICACTA-), Elsevier Procedia Computer Science. https://doi.org/10.1016/j.procs.2015.03.158

Thayakaran Selvanayagam, Suganya S, Puvipavan Palendrarajah, MithunParesithManogarathash, Anjalie Gamage, Dharshana Kasthurirathna (2019), Agro-Genius: Crop Prediction using Machine Learning, International Journal of Innovative Science and Research Technology. No DOI.

V. Patil, Shubham Khadki, Niranjan Dhumal, Tejas Kalbhor, Aniruddha Raje, (2020), Machine Learning Approach for Prediction of Crops, International Journal for Research in Applied Science & Engineering Technology (IJRASET). No DOI.

Viviliya B, Vaidhehi V, (2019), The Design of Hybrid Crop Recommendation System using Machine Learning Algorithms, International Journal of Innovative Technology and Exploring Engineering (IJITEE). DOI: 10.35940/ijitee. B7219.129219.

Zeel Doshi, Subhash Nadkarni, Rashi Agrawal, Prof. Neepa Shah (2018), Agro Consultant: Intelligent Crop Recommendation System Using Machine Learning Algorithms, 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). DOI:10.1109/ICCUBEA.2018.8697349.