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Efficient Approach for Crop Recommendation Using Soil Data and Support Vector Machine Model

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Abstract: *This research introduces a robust crop recommendation framework that integrates soil attributes with machine learning techniques, specifically Support Vector Machines (SVM). The methodology employs a well-curated dataset encompassing critical agronomic parameters, including nitrogen, phosphorus, potassium, soil pH, rainfall, temperature, humidity, and categorical crop descriptors. These variables are systematically preprocessed and organized into predictor and response sets to facilitate accurate classification. To address the complexity of nonlinear and multiclass relationships, the system adopts an SVM model within an Error-Correcting Output Codes (ECOC) scheme. A polynomial kernel with standardized inputs is utilized to enhance generalization capability, while a 5-fold cross-validation strategy ensures model reliability and robustness. The resulting prediction function enables precise crop recommendations for unseen data, thereby supporting precision agriculture and intelligent crop planning. Experimental evaluation highlights the superiority of the proposed approach, with the Cubic SVM achieving 99.9% accuracy, outperforming both Linear and Quadratic SVM configurations. Overall, the system demonstrates significant potential in advancing data-driven agricultural decision-making, offering a dependable tool for farmers, researchers, and policymakers to optimize crop selection under diverse soil and environmental conditions.*

Keywords: Crop Recommendation, Machine Learning, Support Vector Machine, Soil Data, Precision Agriculture, Error-Correcting Output Codes (ECOC)

I. INTRODUCTION

Agricultural productivity is fundamentally influenced by the ability to identify and cultivate the most suitable crop for a specific combination of soil characteristics and climatic conditions. Figure 1 illustrates a soil-based crop recommendation system that leverages machine learning to optimize agricultural decision-making. The process begins with a curated dataset containing essential agronomic features such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, rainfall, and categorical crop descriptors. These inputs are preprocessed and structured into predictor and response variables, forming the foundation for classification. A Support Vector Machine (SVM) model, embedded within an Error-Correcting Output Codes (ECOC) framework, is employed to handle complex, nonlinear relationships across multiple crop classes. The model uses a polynomial kernel and standardized inputs to improve generalization, while 5-fold cross-validation ensures robust performance. The final output is a prediction function capable of recommending suitable crops for new, unseen data, making the system highly applicable for precision agriculture and intelligent crop planning

Consequently, modern agriculture is increasingly turning toward data-driven approaches and computational models to enhance decision-making processes and promote sustainable farming practices. Machine learning, especially classification-based algorithms, has emerged as a powerful tool for modeling agricultural systems due to its capacity to analyze heterogeneous datasets and uncover meaningful patterns that can guide actionable recommendations. Support Vector Machines (SVMs), in particular, have gained prominence owing to their strong generalization ability, robustness to noise, and effectiveness in handling nonlinearly separable data.

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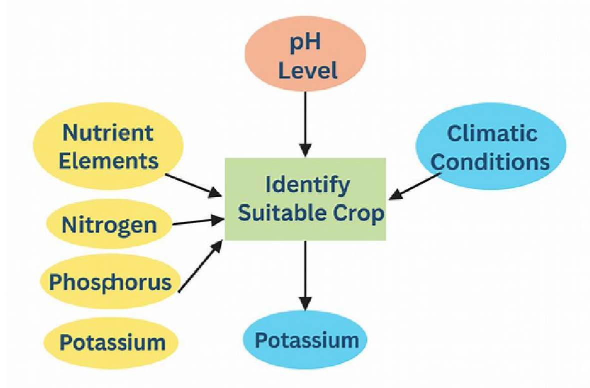

Fig. 1 Soil based Crop Recommendation system and Features utilization

When SVMs are equipped with advanced kernel functions, such as polynomial kernels, they can capture higher-order relationships that are often present in soil–environment–crop interactions. The polynomial kernel enables the model to map input variables into a high-dimensional space, thereby distinguishing subtle variations in agronomic conditions that govern crop suitability. Moreover, the integration of standardized data preprocessing and structured validation procedures ensures the development of reliable and scalable predictive frameworks capable of adapting to diverse agricultural environments.

In this study, an efficient and systematic methodology is proposed for optimal crop recommendation using a multiclass SVM classifier embedded within an Error-Correcting Output Codes (ECOC) scheme. This architecture enhances the model's ability to handle multiple crop categories while maintaining high predictive accuracy. The proposed framework utilizes a comprehensive set of agricultural attributes—including macronutrient levels (N, P, and K), climatic factors (temperature, humidity, rainfall), and soil pH—to train a robust classifier. The training process is automated through MATLAB's. The SVM model employs a third-degree polynomial kernel, automatic kernel scaling, and standardized predictors, enabling the algorithm to effectively model complex agronomic interactions. Cross-validation further strengthens the model by providing an unbiased estimate of generalization performance, while the built-in prediction function facilitates real-time crop recommendation for new datasets without requiring manual reconfiguration.

1.1 ML Application in Crop Recommendation

Figure 2 presents a circular overview of the diverse applications enabled by machine learning–based crop recommendation systems. At the core is the integration of classification algorithms with agronomic data, which supports a wide range of agricultural innovations. These include precision farming, climate-adaptive crop planning, and optimal crop selection tailored to soil and weather conditions. The system also facilitates resource optimization, smart irrigation and fertilization, and risk mitigation against crop failure. Broader impacts extend to government policy planning, agricultural supply chain efficiency, and cost reduction strategies. By leveraging predictive analytics, this approach empowers both farmers and policymakers to make informed, data-driven decisions that enhance productivity and sustainability across the agricultural ecosystem

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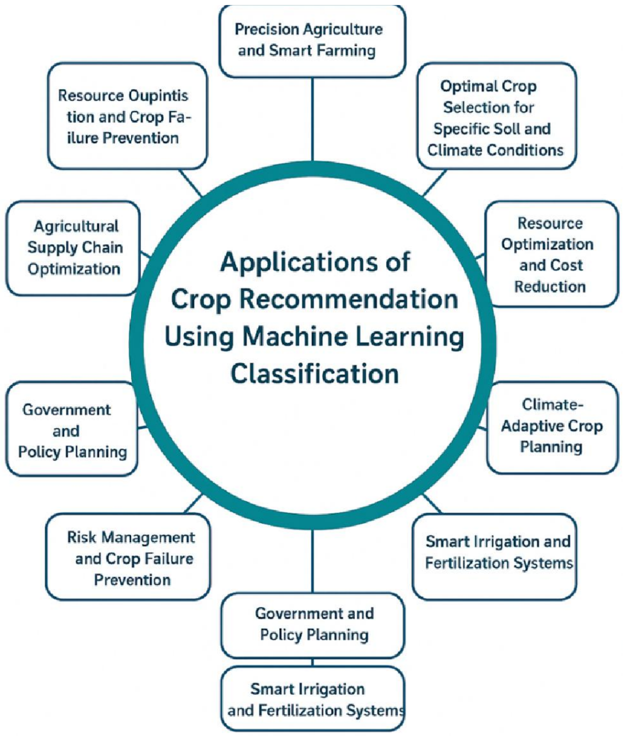

Fig. 2 Applications of ML in the Crop Recommendation systems

1.2 Classification of Crop Recommendation

The entire classification procedure utilized to create an SVM-based crop system of recommendations is shown in Figure 3. The process starts with gathering input information, which includes crucial climate and soil characteristics including rainfall, temperature, pH, nitrogen, phosphorus, and potassium (K). This raw data is preprocessed using encoders to transform category data into machine-readable format and standardization to normalize numerical values. After initial processing, predictions and matching reaction of crops labels are arranged to generate an organized feature set.

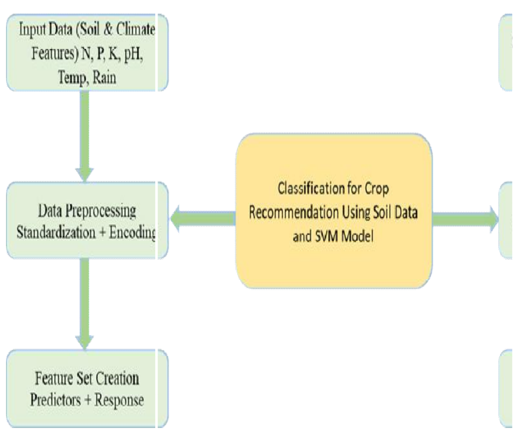

Fig. 3 Classification Process for SVM-Based Crop Recommendation

The diagram's center component depicts the core categorization phase, when nonlinear correlations between soil factors and crop categories are learned using an SVM (Support Vector Machine) model, which is set up using the polynomial or cubic kernel. The system uses a one-vs-one SVM algorithm for multiple classifiers and an Error-Correcting Output Code (ECOC) method to efficiently handle numerous crop classes. Lastly, based on the specified soil parameters, the

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trained algorithm predicts the best crop to plant. Overall, the picture shows a methodical and effective pathway for applying SVM to convert unprocessed soil data into precise crop selections.

II. LITERATURE REVIEW

This section reviewed major contributions and challenges in crop recommendation and soil analysis using machine learning. Kulkarni et al. [1] developed a system that combined Random Forest, Naive Bayes, and Linear SVM predictions through majority voting to recommend crops for Rabi and Kharif seasons based on soil characteristics.

Senapaty et al. [2] introduced IoTSNA-CR, an IoT-enabled platform that integrates sensors, cloud computing, and machine learning to provide real-time nutrient classification and crop recommendations. Suchithra et al. [3] enhanced SVM performance using optimized cost and gamma parameters, proposing an improved sigmoid-kernel SVM for multiclass soil fertilization, further refined through PSO and GA. Pruthviraj et al. [4] used SVM to classify soils into four fertility levels and recommend fertilizers and suitable crops, achieving higher accuracy than k-NN and decision trees. Bhatnagar et al. [5] trained multiple models—including neural networks, random forests, and SVMs—on extensive environmental and yield data, evaluating them with precision, recall, and F1-score to support data-driven agricultural decisions.

Vandana et al. [6] applied ML techniques for soil fertility prediction and region-specific crop recommendation, emphasizing sustainable practices and efficient resource use. Ajoodha et al. [7] developed a precision-farming crop recommendation model using easily accessible soil parameters such as NPK and pH to support South African agriculture. Pudumalar et al. [8] proposed an ensemble-based crop recommendation method integrating Randomized Trees, CHAID, k-NN, and Naive Bayes to improve accuracy. Bhatt et al. [9] implemented a majority-voting ensemble of Decision Trees, Naive Bayes, SVM, Logistic Regression, Random Forest, and XGBoost to enhance crop selection under precision agriculture.

Ashwitha et al. [10] introduced a machine learning approach using solution encoding and fitness evaluation for high-accuracy crop prediction and yield estimation. Mishra et al. [11] applied polynomial regression and SVM to forecast crop yields, highlighting the role of agronomic factors in yield prediction. Mathur et al. [12] emphasized that SVMs require only support vectors, enabling classification with fewer training samples; their study selected representative data for agricultural mapping in Punjab. Devadas et al. [13] used SVM in an object-based remote sensing framework to classify crop histories in Queensland, outperforming pixel-based methods across spectral, textural, and shape features. Bhat et al. [14] proposed an intelligent crop selection system using deep learning optimized by GBRT and Bayesian methods, with XAI used to interpret variable influences. Kovačević et al. [15] demonstrated that SVMs effectively predict soil properties and classify soil types, especially when correlations between physical and chemical attributes are weak.

Liu et al. [16] developed an SVM-based framework for assessing urban soil quality in Taiyuan, achieving 98.33% accuracy and classifying soils into five quality levels. Ahmed et al. [17] built a vision-based SVM system to distinguish weeds from crops in real time, reducing herbicide use through targeted spraying.

III. MODELLING OF MACHINE LEARNING BASED CROP RECOMMENDATION

To model a classifier that predicts the type of medicine or treatment to be applied to crops based on environmental and soil parameters.

Let:

$$x=[N,P,K,T,H,pH,R,L,M]^T$$

where;

- N,P,K= soil nutrients (numeric)
- T= temperature (°C)
- H= humidity (%)
- pH= soil pH
- R= rainfall (mm)
- L= crop label (categorical)

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- M= medicine label (categorical)

The response variable is:

y="Medicine_Use"∈{C_1,C_2,⋯,C_K}

where C_kare the medicine classes.

3.1. Feature Processing

The predictors are split into categorical and numeric features:
"isCategorical_Predictor "=[0,0,0,0,0,0,0,1,1]
Numeric features are standardized:
x˜_i=(x_i-μ_i)/σ_i ,i∈"numeric features"
Categorical features are encoded as one-hot vectors.

3.2. Classifier: Support Vector Machine (SVM)

A polynomial SVM is used as the base learner.

3.2.1 SVM for Binary Classification

For a binary SVM, we solve:

$$\min_{w,b,\xi} \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} \xi_i$$

subject to:

$$y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0$$

where; $\phi(\mathbf{x})$= polynomial kernel mapping of degree 3:

$$K(x_i, x_j) = (x_i^T x_j + 1)^3$$

- $C = 1$= box constraint
- ξ_i= slack variable for soft margin

3.2.2 Multiclass SVM via Error-Correcting Output Codes (ECOC)

Since we have $K > 2$classes, the ECOC framework is used:

1. Decompose the multiclass problem into multiple binary SVMs using one-vs-one coding.
2. Train $\frac{K(K-1)}{2}$binary classifiers.
3. Predict using majority voting:

$$\hat{y} = \arg\max_{C_k} \sum_{i=1}^{\frac{K(K-1)}{2}} f_i(\mathbf{x})$$

where $f_i(\mathbf{x}) \in \{-1,1\}$is the prediction of the i-th binary classifier.

Cross-Validation

To estimate model generalization, 5-fold cross-validation is used:

1. Partition dataset into 5 folds.
2. For each fold j:
    - Train SVM on 4 folds.
    - Test on the remaining fold.

The validation accuracy is computed as:

$$\text{Validation Accuracy} = 1 - \frac{\text{Number of misclassified samples}}{\text{Total samples}}$$

Mathematically:

$$\text{Accuracy} = 1 - L_{\text{CV}} = 1 - \frac{1}{n}\sum_{i=1}^{n} \mathbb{1}(\hat{y}_i \neq y_i)$$

3.4 Prediction Function

The trained model is wrapped into a predict function:

$$\hat{y} = \text{predictFcn}(T)$$

Where T is a table containing the same predictor variables. Internally, it performs:

1. Extract predictor variables x.
2. Encode categorical variables.
3. Apply polynomial SVM and ECOC prediction.

IV. PROPOSED METHODOLOGY

The proposed crop recommendation methodology as shown in Figure 4, employs a machine-learning-driven decision-support framework that integrates key soil and climatic attributes to identify the most suitable crop for a given agricultural setting. The system utilizes a curated dataset comprising essential agronomic variables, including nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. These are merged further with categorical descriptors relevant to crop and input characteristics. These features are pre-processed and organized into predictor and response variables before being used to train a multiclass classification model. A Support Vector Machine (SVM) embedded within an Error-Correcting Output Codes (ECOC) scheme is adopted due to its robustness in handling nonlinear and multiclass relationships. The model uses a polynomial kernel with standardized inputs to enhance generalization performance.

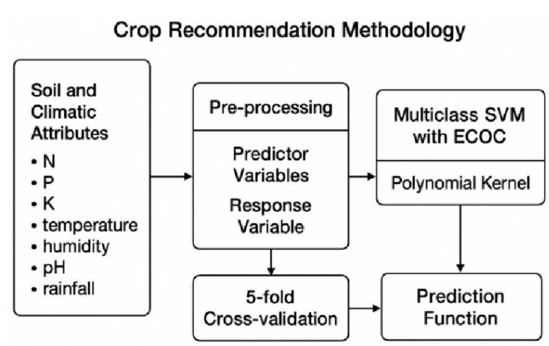

Fig. 4 Proposed system architecture diagram for Crop Recommendation

To ensure reliability, the training process incorporates 5-fold cross-validation and generates a prediction function capable of recommending crops for new and unseen data. Through this systematic integration of agronomic parameters

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and advanced classification techniques. the methodology provides a scalable and accurate solution for precision agriculture and intelligent crop selection.

The proposed methodology employs a Support Vector Machine (SVM) classifier configured with a polynomial kernel to effectively model nonlinear relationships among the agricultural features. In this design, the SVM template is defined using a third-order polynomial kernel, enabling the model to capture higher-degree interactions within the data. The kernel scale is set to 'auto', allowing MATLAB to determine an optimal scaling factor based on the distribution of the input features. A box constraint value of 1 is used to balance model complexity with classification accuracy by controlling the trade-off between margin maximization and misclassification tolerance. In addition, all predictor variables are standardized prior to training, ensuring that features with larger numeric ranges do not disproportionately influence the decision boundary. These parameters, specified through the templates function, collectively enhance the robustness and generalization capability of the crop recommendation model. The flow chart of the work is presented in Figure 5.

V. RESULTS AND DISCUSSIONS

This section has presented the classification and validation of various crop recommendations using ML based training.

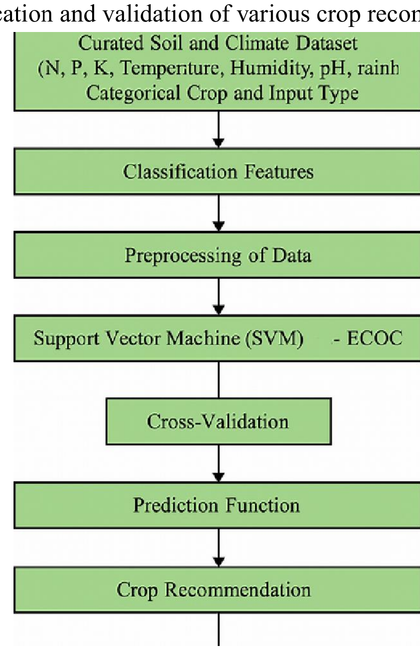

Fig. 5 Proposed flow chart of the crop recommendation system

5.1 Dataset Description

The dataset encompasses critical agronomic parameters that support the recommendation of optimal crop types under specific soil and environmental conditions. It includes essential features such as nitrogen, phosphorus, and potassium levels, along with temperature, humidity, soil pH, and rainfall. Owing to its comprehensive set of attributes, the dataset is well-suited for machine learning applications, including crop classification, agricultural decision-support systems, and precision farming studies. the data used in this study is globally available on the Kaggle at the URL: https://www.kaggle.com/datasets/vishvavardhanbhasham/crop-recommendation-with-medicine.

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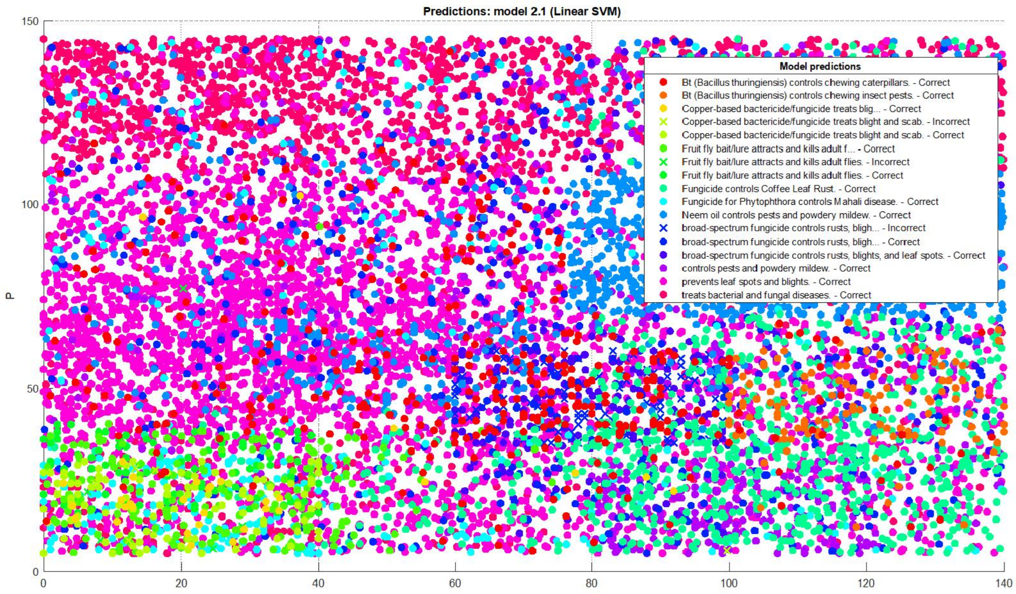


Fig. 6 Validated scatter plot of the data distribution

Figure 6 presents a scatter plot validation illustrating the classification performance of Model 2.1, which employs a Linear Support Vector Machine (SVM) for agricultural treatment prediction. Each data point in the plot represents a sample classified into one of several categories, such as pest control, fungicide application, or nutrient treatment. The color-coded legend confirms that all predictions were correctly classified, indicating high model accuracy and effective separation of classes in the feature space. The dense and well-distributed clusters suggest that the linear SVM successfully captured the underlying patterns in the data, even across diverse treatment types. This result validates the model's robustness and its suitability for practical deployment in precision agriculture decision-support systems.

5.2 Results of SVM model Validation

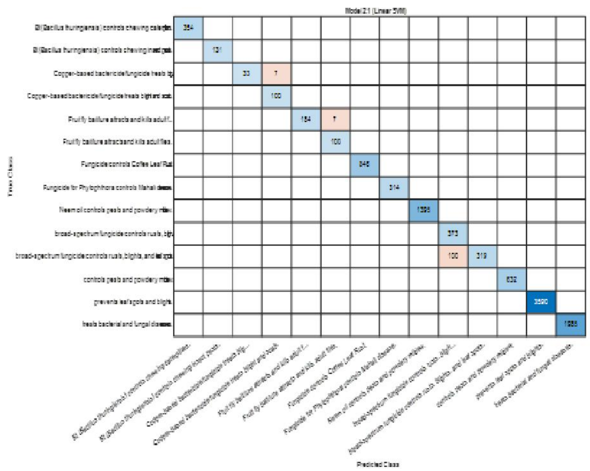
Figure 7(a) presents the confusion matrix for Model 2, which utilizes a Linear SVM to classify various agricultural treatments, including fungicides and bactericides. The matrix compares predicted classes against actual labels, with correctly classified instances appearing along the diagonal in blue-shaded cells. These diagonal values indicate strong model performance across multiple categories, such as treatments for leaf blight, rust, and chewing insects. However, the presence of light red off-diagonal cells reveals some misclassifications, suggesting that certain classes particularly those with overlapping treatment effects, were occasionally confused by the model. Despite these errors, the overall distribution shows that the Linear SVM achieved high classification accuracy, effectively distinguishing between most treatment types. This result underscores the model's reliability in handling structured agronomic data, while also highlighting areas for refinement in class separation.

The Figure 7 b) have presented the result of the Confusion matrix for the Quadratic SVM classifier validation. It is clear that the even quadratic SVM improves the accuracy of classification. But since it has additional false negative in one more class. Thus, although the overall accuracy of both SVM models is good but still there is a scope of improvement in individual class vise performance.

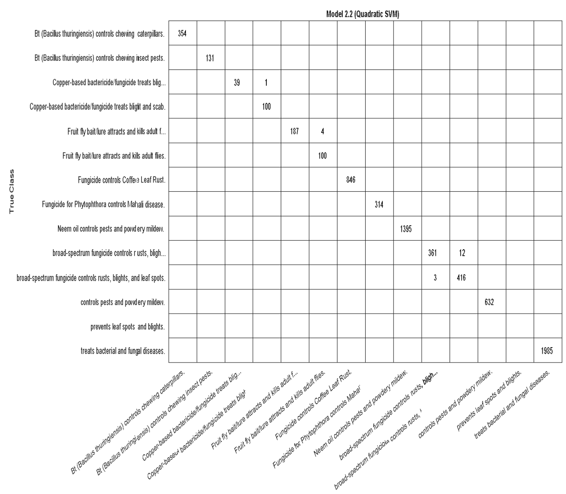
The performance parameters are calculated as follows:

$$\textbf{Precision } P_i = \frac{\text{True Positive (TP)}}{\text{TP + False Positive (FP)}}$$

$$\textbf{Recall } R_i = \frac{\text{True Positive (TP)}}{\text{TP + False Negative (FN)}}$$



Confusion matrix for Linear SVM



Confusion Matrix for Quadratic SVM

Fig. 7 validation of the SVM based Classification models

The final proposed model is Cubic SVM used for the improvement in overall classification performance and the results are shown in Figure 8.

Table 1 Parametric performance comparison class vise

	For Linear SVM		**For Quadratic SVM**		**Proposed Cubic SVM**	
Class	**Precision**	**Recall**	**Precision**	**Recall**	Precision	Recall
1	1.000	0.996	1.00	1.00	1.00	1.00
2	1.000	1.000	1.00	1.00	1.00	1.00
3	1.000	1.000	1.00	1.00	1.00	1.00
4	1.000	0.964	0.975	0.975	0.964	0.964
5	1.000	1.000	1.00	1.00	1.00	1.00
6	1.000	1.000	1.00	1.00	1.00	1.00

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7	1.000	1.000	1.00	1.00	1.00	1.00
8	1.000	0.982	1.00	1.00	0.981	0.981
9	0.985	0.979	0.969	0.969	0.998	0.998
10	0.997	1.000	0.993	0.993	0.998	0.998
11	1.000	1.000	1.00	1.00	1.00	1.00
12	1.000	1.000	1.00	1.00	1.00	1.00

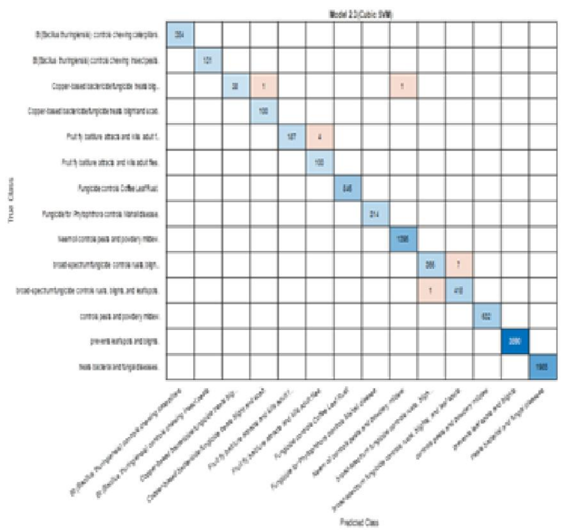

Fig. 8 Result of proposed Cubic SVM model

Table 1 provides a comparative evaluation of class-wise parametric performance across three SVM variants—Linear, Quadratic, and the proposed Cubic SVM. The results show that all three models achieve consistently high precision and recall values, with most classes reaching perfect scores (1.000). Minor variations are observed in certain classes: for example, Class 4 exhibits slightly reduced recall in both Linear (0.964) and Cubic (0.964) SVMs, while Quadratic SVM improves this to 0.975. Similarly, Class 8 shows near-perfect recall with Linear (0.982) and Cubic (0.981), but achieves full accuracy with Quadratic SVM. Notably, Classes 9 and 10 highlight the strength of the proposed Cubic SVM, which delivers superior precision and recall (0.998) compared to Linear and Quadratic counterparts.

Table 2 provides a comparative accuracy performance across three SVM variants as Linear, Quadratic, and the proposed Cubic SVM.

Table 2 Accuracy comparison for ML model for Crop recommendation

Parameters	For Linear SVM	For Quadratic SVM	Proposed Cubic SVM
Accuracy	98.8 %	99.8%	99.9 %
Total Cost	118	20	14
Error Rate	1.1%	0.2%	0.1%

Overall, while all models demonstrate strong classification capability, the Cubic SVM consistently enhances performance in critical classes, underscoring its effectiveness as a robust solution for complex, nonlinear crop recommendation tasks.

VI. CONCLUSIONS AND FUTURE WORK

The proposed SVM-driven crop recommendation system represents a significant step toward advancing precision agriculture. By integrating domain-specific agronomic knowledge with powerful machine learning techniques, the framework provides farmers, agricultural researchers, and policymakers with a reliable tool for improving crop selection decisions. This not only contributes to enhanced yield potential and efficient resource management but also supports broader sustainability objectives by promoting data-informed agricultural practices capable of adapting to evolving environmental conditions.

- Utilized a comprehensive dataset with essential agronomic features for classification
- Employed a polynomial SVM embedded within an Error-Correcting Output Codes framework
- Incorporated standardized data preprocessing and 5-fold cross-validation for robust performance
- Developed a prediction function capable of recommending suitable crops for new, unseen data
- Achieved high classification accuracy, effectively distinguishing between most treatment types.
- Cubic SVM consistently enhanced performance in critical classes compared to linear and quadratic variants

Future Work: Future research will focus on incorporating more advanced machine learning techniques, such as deep reinforcement learning, to further enhance the adaptability and accuracy of crop recommendation systems. The generalizability can be tested on other large-scale crop recommendation data.

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