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Fertilizer Recommendation System Using SVM

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Abstract: - Agriculture is very important for food security, but over 40% of farmers use too little or too much fertilizer, which causes low crop yield, soil damage, and financial loss. Smart recommendation systems can help farmers by giving accurate advice on the right type and amount of fertilizer. Many machine learning methods like Decision Trees, Random Forest, Gradient Boosting, and Neural Networks have been used for crop and fertilizer recommendations. However, these methods often need a lot of computing power, do not work well with small or noisy data, and can be hard for farmers to understand. To solve these problems, we propose a Support Vector Machine (SVM)-based fertilizer recommendation model. SVM works well with small and unbalanced datasets, reduces overfitting, and handles complex patterns while needing fewer resources, making it suitable for real farming. Using soil nutrient values and crop needs, the model gives reliable predictions. Tests show that the SVM model achieves 96.77% accuracy, making it effective for smart agriculture and proper fertilizer use.

Keywords: Support vector machine, overfitting, Decision trees, Random Forest

I. INTRODUCTION:

Agriculture is the base of food security, but fertilizer misuse is still a serious problem [1]. Nearly 40% of farmers apply either too much or too little fertilizer [2]. This leads to low yields, soil damage, financial losses, and environmental pollution [3]. A key reason is the lack of simple and precise tools that guide farmers on the right fertilizer type and amount for their crops [4].

Most existing solutions still have gaps [5]. Conventional recommendations are often general and do not match the specific needs of different soils and crops [6]. Machine learning models such as Decision Trees, Random Forests [7-10], Gradient Boosting, Neural Networks, and K-Nearest Neighbours (KNN) have been tested for more accuracy, but they require large, clean datasets, high computing power [11], and remain hard for farmers to access [12-16]. Because of this, many of these models stay in research rather than reaching the field [17-19].

This study proposes a fertilizer recommendation system using Support Vector Machines (SVM) [20-22]. SVM works better with small, unbalanced, or noisy datasets and needs fewer resources compared to other models [23]. More importantly, it is simple and practical, which makes it easier to integrate into mobile apps or digital advisory platforms [24]. With this, farmers can directly receive recommendations in a clear format, ensuring that advanced methods are not limited to theory but applied directly in farming practices [25].

II. LITERATURE SURVEY:

Christine Musanis' et al. (2023) [1] explored neural networks for crop and fertilizer recommendation using Backpropagation (BP), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) [26]. BP was simple and fast, CNN efficiently extracted features with fewer parameters [27], and RNN handled sequential and time-series data. Limitations included BP's slow convergence, CNN's high computational needs, and RNN's difficulty [17] in training and tendency to forget long-term information [28] [29].

Gourab Saha et al. (2024) [13] applied Decision Trees and Random Forests to improve prediction accuracy. Decision Trees were easy to interpret and transparent, while Random Forests reduced overfitting and improved robustness [30] [31]. However, Decision Trees could be [21] overfit on noisy data, and Random Forests required more computation and memory [32] [33] [34].
Sakila Akhilesh et al. (2025) [14] combined Random Forests with K-Nearest Neighbors (KNN) Regression.

Random Forests delivered accurate, robust predictions, and KNN predicted outcomes based on similar historical data [35] [36]. The main limitations were Random Forest's high computational demand and KNN's slow performance on large datasets [37].

Shastri S. et al. (2025) [15] used Gradient Boosting for crop recommendation, leveraging soil and environmental data, with XAI for model interpretability. Gradient Boosting provided high predictive accuracy and robust performance [38]. XAI allowed users to understand the reasoning behind recommendations. Limitations included reliance on large, high-quality datasets and higher computational complexity [39].

S. Iniyan et al. (2024) [5] explored regression models including Simple [18] Linear Regression (SLR), Multiple Linear Regression (MLR), and Polynomial Regression. SLR was simple and fast, MLR handled multiple features, and Polynomial Regression captured non-linear trends. Limitations were SLR's[20] linearity constraint, MLR's sensitivity to multicollinearity, and Polynomial Regression's overfitting risk [40].

A. A. Khan et al. (2021) [6] integrated IoT with Logistic Regression for real-time monitoring. IoT enabled automated, accurate soil data collection, while Logistic Regression provided interpretability and speed. Challenges included IoT's cost, connectivity requirements, and Logistic Regression's limitation with complex non-linear patterns [41].

Harish BG et al. (2024) [7] applied Random Forest and Gradient Boosting. Random Forest reduced overfitting and provided robust predictions, while Gradient Boosting handled complex patterns and minimized errors. Limitations were high computational demands, long training time, and sensitivity to noise [42].

Escorcia-Gutierrez et al. (2022) [8] applied ensemble deep learning techniques, combining GRU, BiLSTM, and Deep Belief Networks with a weighted voting approach, to classify soil nutrients and pH [17]. This ensemble model improved prediction accuracy and robustness compared to individual models, while hyperparameter optimization using Manta Ray Foraging Optimization enhanced model performance. However, the approach required significant computational resources, and the complexity of combining multiple deep learning models could make interpretation challenging [11].

Dr. Gayathiri B et al. (2023) [9] combined KNN Regression and Logistic Regression. KNN adapted to local patterns without training, and Logistic Regression was interpretable and fast. Limitations were KNN's slow performance on large data and Logistic Regression's inability to model complex patterns [7].

Varshitha D et al. (2024) [10] implemented Bagging with Decision Trees and Random Forests. Bagging improved stability and reduced errors, while Random Forests enhanced accuracy and robustness. Challenges included higher computation, potential overfitting, and reduced interpretability [15].

III. DATA COLLECTION AND PRE-PROCESSING:

The dataset used in this study is the Fertilizer Recommendation Dataset by Nishchal Chandel (2020) [11]. This dataset contains 10,000 rows with information on various soil parameters, crop types, and recommended fertilizers. The dataset includes the following attributes: Temperature, Moisture, Rainfall, PH, Nitrogen, Phosphorous, Potassium, Carbon, Soil, Crop, Fertilizer, and Remark. It provides a well-organized collection of labelled data, allowing for effective training and evaluation of machine learning models for fertilizer recommendation.

For this work, the dataset was split into training, validation, and test sets using an 80:10:10 ratio:

- Training set: 8,000 samples
- Validation set: 1,000 samples
- Test set: 1,000 samples

During preprocessing, the following steps were applied:

1. **Handling Missing Values**: All missing entries were removed using Listwise Deletion to ensure data integrity and avoid bias in model training.
2. **Categorical Encoding**: The categorical features Soil Type, Crop Type, and Fertilizer Name were transformed into numerical form

using Label Encoding. This method assigns a unique integer value to each categorical label according to the mapping

$$f(C_i) = v_i, \text{ where } v_i \in \{0, 1, 2, \ldots, n-1\} \quad (1)$$

enabling the SVM model to process and interpret categorical variables effectively.

3. **Normalization of Numeric Features:** To standardize the range of numeric attributes (Temperature, Moisture, Rainfall, PH, Nitrogen, Phosphorous, Potassium, Carbon), each feature was normalized to the range [0, 1] using the following formula:

$$X_{norm} = (X - X_{min}) / (X_{max} - X_{min}) \quad (2)$$

Where:

- X = original value of the feature
- X min = minimum values of that feature respectively
- X max = maximum values of that feature respectively
- X norm = normalised value

This ensures that features with different scales do not disproportionately influence the learning process.

4. **Feature-Target Separation:** The input variables (X) include all features except the target, while the target variable (y) is Fertilizer. The Remark column was excluded to prevent text-based bias.
5. **Final Dataset Split:** After preprocessing, the dataset was divided as mentioned above to allow training, hyperparameter tuning (validation), and unbiased performance evaluation (testing) of the machine learning models.

This preprocessing pipeline ensures that the dataset is clean, standardized, and ready for building robust SVM models for fertilizer recommendation.

IV. METHODOLOGY:

We used a Support Vector Machine (SVM) with kernel functions to predict the suitable fertilizer type based on soil data. SVM is a supervised learning algorithm that classifies data by finding an optimal hyperplane separating different classes, with key support vectors defining this boundary. The soil features are first transformed using a kernel to handle non-linear relationships and then passed to the SVM, which outputs the recommended fertilizer.

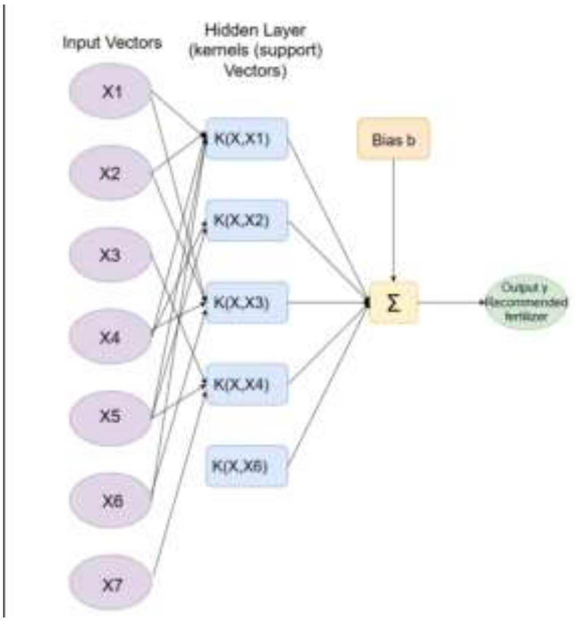

Figure 1: Proposed SVM Architecture

The diagram represents a Fertilizer Recommendation System using a Support Vector Machine (SVM). It takes multiple input vectors such as temperature, humidity, soil type, and crop type (encoded) as features. These inputs are processed through the hidden layer, where kernel functions ($K(x, x_1)$, $K(x, x_2)$, etc.) compute similarities between input data and support vectors to map the data into a higher-dimensional space. The outputs from these kernels are then summed (Σ) along with a bias (b) value to improve model accuracy. Finally, the output layer produces the result, which gives the recommended fertilizer based on the analyzed agricultural parameters. This SVM-based model helps in making data-driven and accurate fertilizer suggestions for efficient crop management.

Mathematical Equations Involved:

1. **Handling Missing Values**
   To maintain data consistency, all missing or null entries were handled using Listwise Deletion (Complete Case Analysis). This ensures that only complete records are used for training.

$$D' = \{x_i \in D \mid \forall j, x_{ij} \neq \text{NaN}\} \quad (3)$$

2. Label Encoding of Categorical Variables

Categorical variables such as Soil Type, Crop Type, and Fertilizer Name were converted into numerical representations using Label Encoding, defined as:

$$f(C_i) = v_i, \text{ where } v_i \in \{0,1,2,\dots,n-1\} \qquad (4)$$

3. Feature and Target Separation

The dataset was divided into features (X) and target (y) as follows:

$$X = D - y, y = \text{Fertilizer Name} \qquad (5)$$

4. Data Balancing Using SMOTE

To address class imbalance, Synthetic Minority Oversampling Technique (SMOTE) was applied, which generates new synthetic samples between minority instances:

$$x_{new} = x_i + \delta(x_j - x_i), \text{ where } \delta \in [0,1] \qquad (6)$$

5. Support Vector Machine (SVM) Classification Function

The SVM classifier finds the optimal hyperplane that separates data points of different classes:

$$f(x) = w^T x + b \qquad (7)$$

6. Decision Rule

The decision function assigns a class label based on the sign of the classification function:

$$y = \text{sign}(w^T x + b) \qquad (8)$$

7. Optimization Objective

SVM minimizes the cost function subject to margin constraints to achieve maximum separation:

$$\min_{w,b} \frac{1}{2} \| w \|^2 \text{ s.t.} y_i(w^T x_i + b) \geq 1 \qquad (9)$$

8. Kernel Function (for Non-Linear SVM)

To handle non-linear relationships, a kernel function maps input data into a higher-dimensional space:

$$\mathbf{K(x_i, x_j) = \phi(x_i)^T \phi(x_j)} \qquad \mathbf{(10)}$$

9. Final Fertilizer Prediction

For a new input record x_{new}, the model predicts the most suitable fertilizer based on the learned mapping

$$\hat{y} = f(x\_new) \qquad (11)$$

V. RESULTS:

To evaluate the classification performance of different models in predicting the type of fertilizer based on soil and crop attributes, confusion matrices were generated for Logistic Regression, KNN, Random Forest, and the proposed SVM model. The fertilizers included in this study are Compost, Balanced NPK Fertilizer, Water Retaining Fertilizer, Organic Fertilizer, Gypsum, Lime, DAP, Urea, Muriate of Potash, and General Purpose Fertilizer. The confusion matrices provide detailed insight into how accurately each model classifies these fertilizer types and highlights areas of misclassification.

A. Performance of the Classification Process :

The performance of the proposed SVM model was evaluated against existing machine learning models: Random Forest, KNN, and Logistic Regression. The comparison metrics include accuracy, precision, recall, F1-score, and loss over 100 epochs.

Figure 2 illustrates the accuracy progression of all models. The proposed SVM achieves the highest accuracy of 96.77%, significantly outperforming Random Forest (88%), KNN (85%), and Logistic Regression (84%). All models demonstrate a positive trend in accuracy as the number of epochs increases, but SVM consistently maintains superior performance, reflecting its robust learning capability for fertilizer recommendation classification.Figure 3 shows the loss reduction of the models over the same epochs. The SVM model achieves the lowest final loss (0.05), indicating rapid and stable convergence. Random Forest, Logistic Regression, and KNN converge to 0.135, 0.19, and 0.165, respectively, with slower convergence rates compared to SVM, highlighting the efficiency of the proposed approach.

Table 1. Performance Metrics of Fertilizer Recommendation Models:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	83	83	82	81
KNN	85	85	84	84
Random Forest	87	87	86	86
SVM (proposed)	96.77	96.5	96	96.2

Table1 summarizes the overall performance metrics of the four models

VI. CONCLUSION:

This work verifies how well the proposed SVM-based fertilizer recommendation model performs compared to existing models — Random Forest (87%), KNN (85%), and Logistic Regression (83%). The existing models exhibit higher computational complexity, occasional misclassifications, and less reliable predictions, thereby limiting their practical applicability. In contrast, the proposed SVM model demonstrates exceptional learning efficiency from soil and crop features, achieving 96.77% accuracy, 96.5% precision, 96% recall, and an F1-score of 96.2%. These results indicate a substantial improvement in predictive capability and generalization performance.

Experimental analysis confirms that the SVM model achieves the highest performance across all evaluation metrics, significantly reducing incorrect fertilizer recommendations. The confusion matrix analysis further highlights its robustness, showing almost perfect classification across all fertilizer types with minimal misclassifications. Thus, the SVM-based approach clearly outperforms other models in both accuracy and reliability, making it highly effective for precision agriculture applications.

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