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A Machine Learning Model for Crop Yield Prediction

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Abstract

India is one of the largest global agricultural countries. Instead of that, the farmers face a lot of challenges in crop production, despite its crucial economic value. These issues have an immediate impact on the livelihoods of farmers making it imperative to enhance agricultural output to meet the global food demand. To enhance the productivity, the farmers need to determine which crop are best suited for their specific fields. A proposed solution is the crop recommendation system which forecasts the idea type of crop for cultivation by monitoring various parameters and constraints. Previous research has focused on numerous agricultural issues such as cost, water, and soil management fruit maturity, plant diseases, soil mining, and other farm sectors. These suggestions are dependable and based on, measurable evidence including soil pH, humidity, rainfall, temperature, and soil nutrient concentration (N, P, and K). However, they lacked a thorough evaluation on machine learning role in crop recommendation. By using the Support Vector Machine (SVM) approach, the proposed model can determine the most profitable crop under some current conditions. The model is first trained on a dataset using pre-recorded values, enabling it to predict the crop type independently. Selecting the appropriate crop type can enhance total yield, promoting agricultural sustainability and addressing the global food demand. Incorporating real-time data from IoT sensors, satellite images improve the efficiency of the model, using advanced machine learning techniques such as SVM helps in precise crop prediction, assisting in optimizing resource usage, also increasing the economic viability of the farmers.

Keywords—Machine Learning Model, Yield Prediction, Support Vector Machine (SVM), Crop Recommendation Model, Agricultural Factors

I. INTRODUCTION

India, a major player in global agriculture, faces the critical challenge of increasing farm productivity. Agriculture is India's prime occupation. Approximately half of country's workforce is employed in agriculture, either direct or indirect manner. Despite its importance, many farmers struggle with low productivity and incomes, which is exacerbated by unpredictable climate conditions and suboptimal farming practices. The Gross Domestic Product is over 20% derived from agriculture. India ranks among the top agricultural-producing nations in the world, yet its farm productivity is still low. Farmers need to about the suitable crop in a certain field to enhance productivity and to increase income. The need for a Crop Recommendation Model comes out from the difficulties of farming, which involves managing various factors such as soil materials, weather forecast, and nutrient resources A data-driven process can provide more accurate and efficient recommendations, which is used to help farmers to make decisions that maximize productivity and profitability (Banavlikar, Mahir, Budukh & Dhodapkar, 2018).

For a Crop Recommendation Model, some factors should be noticed. In soil pH, the acidity or alkalinity affects the availability of nutrient and the action of microbial. For Humidity, the moisture present in the air, has an impact on plant transpiration and disease susceptibility. The amount of rainfall is vital for water supply. The temperature effects highly on plant growth rates. The ratio of nitrogen (N), phosphorus (P), and potassium (K) are crucial for plant growth. From the previous studies we can get to know about various information of agriculture like cost management, water and soil conservation, disease control, and crop ripeness, in crop recommendation using Machine learning. But now using Machine learning, we can analyze large datasets to uncover patterns and relationships that are not done by through traditional methods (Hina & Hasan, 2022).

To find out the most lucrative harvest under the current circumstances, we would employ the SVM (Support Vector Machine) methodology of the machine learning approach. The model would be trained on a certain supervised dataset with pre-estimated values, and it would then be able to predict the type of crop on its own. An efficient machine learning algorithm has the properties to handle big datasets with various input variables, manage missing data, and minimize overfitting, all of which can be essential in agricultural applications. There are certain advantages of employing SVM. SVM is capable of excellent precision in tasks such as classification, making it a viable option for crop prediction. SVM is capable of handling both linear and nonlinear data, providing it to adjust for the complex interactions between numerous agricultural criteria. It provides high precision (Ericksen, Ingram & Liverman, 2009).

Building the crop recommendation model comprises numerous steps. The first step is to collect dataset. Next, interpolation or imputation techniques can be used to replace in missing values. The data is then standardized or normalized to verify that all the parameters are perfect. Next, the significant and relevant features are selected to decrease the complication of the proposed model and to improve its performance. The subsequent step was to train the model, with the pre-processed dataset. The dataset was divided in two different set in 4:1 ratio - training and a testing set. The training set was employed to train the model, and the testing set was used to evaluate the model's performance. The parameters of the model were optimized using techniques such as grid search or random search to get the best possible accuracy.The efficiency of the proposed model was evaluated using metrics such as accuracy, precision, recall, and F1-score. If the model functions perfectly, it is then applied to real-world scenarios.

To implement the crop recommendation system in such a way that is easy to understand and handle by the farmers. Mobile application or a web-based platform can be used. The application should provide an easy-to-use interface where farmers can input their field constraints and receive crop recommendations. Crop yield Recommendation system offers some useful benefits. High-quality dataset is needed for training for a perfect model. Farmers should understand about new technologies (Nair, King, Witter, Sohngen & Fausey, 2011). Additional studies might investigate by utilizing additional methodologies for machine learning, including deep learning and ensemble methods, to enhance crop recommendation accuracy. Moreover, the Crop Recommendation Model can include recommendations for pest control, irrigation management, and fertilization schedules, providing a comprehensive decision- support system for farmers (Prasad, Anup, Singh, Chai & Kafatos, 2005).

In conclusion, the proposed Crop Recommendation Model used to revolutionize crop selection, elevate yields, and uplift farmer incomes holds immense promise in addressing the challenges of low farm productivity and meeting the increasing global food demand (Khairunniza-Bejo, Mustaffha & Ismail, 2014).

II. RELATED WORKS

Crop prediction and recommendation are crucial for quick decision-making at the national and regional levels (e.g., the EU level). Farmers may make decisions about what to grow and when by using an accurate crop recommendation model. Among the requirements for exclusion used in the analysis of the previously recovered publications is whether a publication is a traditional review paper or a survey. In (Chlingaryan, Sukkarieh & Whelan, 2018), the authors conducted review research on using machine learning to estimate nitrogen status. This study demonstrates that the improvements in ML techniques and sensor technology has led an affordable agricultural sector solution. The authors and colleagues surveyed papers on machine-learning models related to agrarian production prediction based on meteorological characteristics (Elavarasan, M Durai Raj, Sharma, Zomaya & Srinivasan, 2018). The study suggests a comprehensive approach to identify other factors influencing crop productivity. According to (Liakos, Busato, Moshou, Pearson & Bochtis, 2018), in 2018, a review paper was released regarding the use of machine learning methodology in the agriculture industry. Publications on soil, water, livestock, and agricultural management were used in the analysis. The authors of (Li, Lecourt & Bishop, 2018) conducted a review on fruit to determine the best harvest time and forecast production. The paper (Mayuri & Priya, 2018) discussed the difficulties and approaches found in the field of machine learning and image processing in the agriculture industry, particularly regarding disease detection. In (Matsumura, Gaitan, Sugimoto, Cannon, & Hsieh, 2015), A group of authors demonstrated various machine learning techniques and how they might be used in plant biology. In (Gandhi & Armstrong, 2016), A review article on cultivation engineering was done by using data mining technique. According to (Beulah, 2019), the several data mining methods for predicting crop productivity were examined by the writers. They concluded that using data mining techniques could solve the problem of predicting agricultural productivity. The paper proposed in (Banavlikar et al., 2018) a crop recommendation system prototype employing neural networks, integrating soil sensors through an ESP8266 to a Raspberry Pi for data aggregation and coordination. In (Sahu, Chawla & Khare, 2017), a paper employs a Random Forest algorithm within the Hadoop framework utilizing soil parameters like type, reaction, and nutrients for predicting harvest outcomes. Implemented on Ubuntu 14.04 LTS along with Hadoop 2.6.0, the model achieves 91.43% accuracy, handling large datasets through the MapReduce programming model for efficient processing. One of the studies in Kerman, Iran, according to (Nosratabadi et al., 2020), compares the effectiveness of two hybrid machine learning techniques, a grey wolf optimizer and an artificial neural network with an imperialist competitive algorithm, for crop yield prediction in a large, irrigated area.

SVM algorithm was employed in the research work (Kumar, Singh, Kumar & Singh, 2015), in which the Hadoop framework was utilized and as a constraints soil parameters such as type, reaction, and nutrients for predicting harvest outcomes was implemented. (Kumar et al., 2015) employed SVM method for rice yield prediction in India. This work highlighted the usefulness of SVM with polynomial kernel functions in accomplishing an efficient prediction accuracy for rice yield. The work by (Markowska-Kaczmar & Kosturek, 2021) made a comparison study between SVM and Extreme Learning Machines (ELM). Their findings suggested that ELMs have a faster training performance compared to SVM for maintaining comparable prediction accuracy. In the research work, it has been shown that both Artificial Neural Network (ANN) and SVM can be effective for crop yield prediction. The study by Patil et al. demonstrated that ANN achieved a good performance accuracy than SVM in some of the specific scenarios. Now a days, the Crop Selection Method was developed for choosing the certain crop to be planted during a season. Crops which can be planted throughout the season, can have a higher net yield rate. Using characteristics (e.g., weather, soil type, water density, and crop type) as influences, the suggested method solves crop selection based on predictable yield.

Combining SVMs with other ML algorithms in ensemble learning frameworks might lead to further improvements in prediction accuracy and robustness. In (Paul, Vishwakarma, & Verma, 2015), the work was conducted employing Rapid-Miner 5.3. The model was evaluated using SVM, with the pre-processed data.

In 2022, according to (Elbasi et al., 2023), a project's goal was to recommend crops to farmers using a Decision Tree Classifier. It involves preprocessing a comprehensive dataset covering all Indian states, contrasting with the old system focused on a single state.

In one of the recent approaches, the data-loading process in (Deshpande, Khandagle & Kolhe, 2023) involves cloud utilization and initial summarization using mean, variable variance, entropy, and plotting. Denoising removes junk and null values. To test the model, the dataset is divided into train and test sets.

Based on our study of review articles—the noteworthy ones are included in this section—this research is the first SLR to use machine learning to address the problem of agricultural production prediction. Most of the examined research focused on a particular area of crop prediction, and the survey studies that are currently in place did not thoroughly examine the literature.

III. RESEARCH METHODOLOGY

In the realm of Machine Learning, the cornerstone of achieving superior accuracy lies in the acquisition of top-tier and multifaceted data. Preceding the modelling phase, data preprocessing and feature engineering emerge as indispensable procedures, serving to rectify, systematize, and metamorphose datasets, thereby curtailing inaccuracies to their barest minimum. The following Fig. 1 shows the flow diagram of the model used.

A. Data Acquisition and Preprocessing

The farmers involve with a user-friendly interface to put critical data concerning soil quality and current weather conditions for the agronomic context. Focusing for a crop recommendation system of specific geographical region, the dataset should be customized by the provision of geographical coordinates, essential for precise weather forecasts. The pre-processing of the dataset is a crucial step for validation and standardization the data, anomalies in dataset, potential errors, or missing values. This ensures reliability of the dataset, useful for training in machine learning model and enhancing the predictive performance. Table 1 describes the steps involved in Data Preprocessing.

Table 1: Data Preprocessing Steps

Steps	Description
Data Cleaning	Identifying and rectifying inaccuracies, removing duplicates, and handling missing values.
Data Normalization	Rescaling numerical data to a standard range (e.g., [0, 1]) to ensure uniformity.
Data Transformation	Converting categorical variables into numerical formats (e.g., one-hot encoding).

B. Feature Engineering

Creating informative features from existing dataset, to improve model performance, following techniques as mentioned in Table 2.

Table 2: Feature Engineering Techniques

Technique	Description
Feature Selection	Identifying the most relevant features using methods such as Recursive Feature Elimination (RFE) and LASSO.
Feature Creation	Constructing new features based on domain knowledge, such as aggregating data points or deriving metrics.

C. Model Selection

According to characteristics of the dataset, appropriate ML algorithms are selected, amongst which are:

There are supervised learning models: linear regression, decision trees, random forest, support vector machines (SVM), and neural networks.

Unsupervised Learning Models: K-Means Clustering, Principal Component Analysis (PCA), and Autoencoders.

D. Model Training and Testing Training

Pre-processed and engineered dataset is used to train the chosen model by involving techniques such as k-fold cross-validation. Metrics used are accuracy, precision, recall, F1-score, area under the ROC curve (AUC-ROC), and more to measure the performance of the model.

E. Support Vector Machine Classifier

The Support Vector Machine methodology is a supervised max-margin classification technique. It is best suited technique for both regression and classification application. It signifies the data by a set of pairwise similarity comparisons between the data points through the use of a kernel function. It draws a decision boundary inside the n-dimensional event space when to differentiate among different categories. This decision boundary is called hyperplane that is designed to precisely enhance the distance between classes. This is also called a support vector.

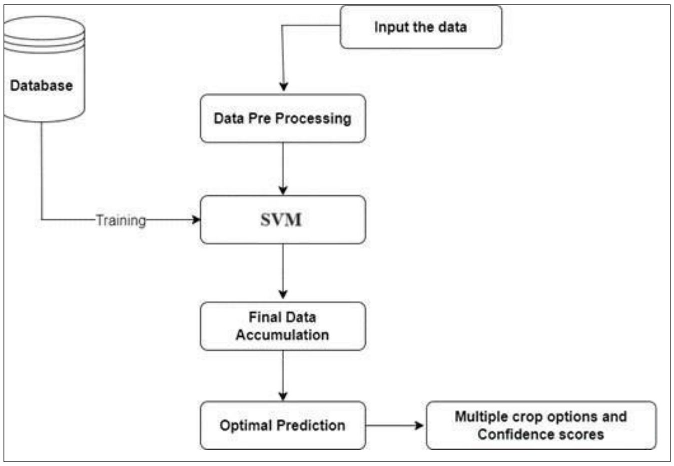

Fig. 1: Flowchart of the Proposed Model

F. Experimental Set Up

The investigational setup for the proposed system is organized into three distinct components: Dataset collection, hardware configuration, and software implementation. Primarily, the dataset was precisely gathered from indigenous locations within Indian villages, confirming real-time relevance and authenticity. For model training and learning processes, an NVIDIA GPU server workstation featuring a 12-core Intel Xeon CPU, 32 GB of RAM, and a 1 TB HDD was employed. The model was performed using Python version 3.9.7 along with the TensorFlow framework, leveraging their capabilities to execute the system flawlessly. Detailed specifications of the hardware and software used in the proposed system are provided in Table 3.

Table 3: Experimental Setup for the Proposed System

Hardware/Software	Specification
GPU	12 Intel Xeon CPU, 32 GB of RAM memory, 1 TB HDD
Python 3	Jupyter notebook
Dataset	Historical dataset

IV. RESULTS ANALYSIS

A. Dataset Used

Let us delve into each factor and its impact on crop production:

- *N (Nitrogen):* Nitrogen is an essential nutrient for the growth of the plants. It consists of chlorophyll which is vital for photosynthesis (Nitrogen in Plants). It also plays the role of a building block of amino acid synthesis for proteins synthesis which is an essential ingredient for plants. Structural proteins fortify plant cells, while enzymatic proteins facilitate essential biochemical reactions vital for sustaining life. A sufficient nitrogen supply fosters robust plant growth, foliage development, and overall crop yield. Conversely, nitrogen deficiency stunts growth and diminishes yields.
- *P (Phosphorus):* Phosphorus is indispensable for energy storage and transfer within plants, DNA and RNA synthesis, and root development (Phosphorus in Plants). As a core element of DNA, the genetic blueprint of all organisms, phosphorus plays a crucial role. It also forms part of RNA, which decodes DNA's genetic instructions to synthesize proteins and other essential molecules for seed production, plant structure, and genetic inheritance. Phosphorus bonds contribute to the structure of both DNA and RNA. Inadequate phosphorus availability hampers energy transfer, flowering, and fruiting. Adequate phosphorus supports robust root systems, flowering, and fruit maturation.
- *K (Potassium):* Potassium participates in photosynthesis, enzyme activation, and plant water uptake (Potassium for crop production). It facilitates water, carbohydrate, and nutrient transport within plant tissues. Potassium's role in enzyme activation influences starch, protein, and adenosine triphosphate (ATP) synthesis. ATP production regulates photosynthetic rates. Sufficient potassium enhances plant resilience against stress, improves water utilization efficiency, and bolsters disease resistance. Potassium deficiency diminishes crop quality and yield.
- *Temperature:* It profoundly affects plant metabolic processes such as photosynthesis, respiration, and transpiration. The climate primarily determines crop yield potential (Agrometeorology: Temperature and Plant Growth). Optimal growth of different crops hinges on specific temperature requirements. Extreme temperatures—either excessively high or low— adversely impact crop development, flowering, and fruit setting.
- *Humidity:* It indicates transpiration rates in plants, influencing water loss (How Humidity Affects The Growth of Plants). Poor air circulation or excessive humidity impedes nutrient uptake from soil and disrupts transpiration, eventually leading to plant decay. Various crops exhibit varying humidity preferences. High humidity levels foster disease proliferation, while low humidity increases water loss. Maintaining optimal humidity levels is crucial for sustained crop health.
- *pH (Soil Acidity/Alkalinity):* Soil pH significantly affects nutrient availability and microbial activity. pH preferences for plants are different. The rate of acidity or alkalinity in the soil should be within the ideal ranges. The plant growth and productivity can be disrupt for over dose of these components.
- *Rainfall:* Water is the most essential part of agriculture. The Rainfall is the chief water source for agriculture, and vital for crop health (How Rainfall

Affects Crop Health). Acceptable level of rainfall ensures plants to have adequate amount of water and nutrients. Optimal amount sustains healthy plant growth and plentiful, nutritious yield. Insufficient rainfall causes lack strain, while extreme rainfall causes waterlogging and nutrient leakage.

- *Label (Crop Type):* It signifies a precise crop under cultivation. Every crop distinctly entails nutritional, water, and environmental requirement. Crop types is vital to be aware of for the optimal productivity.
- *Crop_ID:* It classifies discrete crops within datasets to distinguish the different factors of the crop analysis.

In summation, nutrient levels (N, P, K), temperature, humidity, soil pH, and water availability (rainfall) play fundamental parts in determining crop productivity in a certain region and for a certain parametric constraint. Optimization of those factors generates the growth of the crops.

This proposed model focuses user-friendliness by letting users in making decisions, consequently making agricultural intelligence. The user-friendly interface decreases technological challenges equipping farmers with varying technical skills.

Investigators have employed SVM classifier for an optimized performance of the model. The dataset preprocessed, and then trained by meticulous scrutiny of each training parameters. The performance of the model has been discussed below:

The performance of the system denotes the predictions aligning with actual outcomes. The confusion matrix of the model's performance demonstrates higher precision compared to alternatives. A total of 780 rows were tested, with accuracy continually improving through iterative training. The model achieved peak accuracy of 96% underscoring the significant impact of training parameters on performance. Therefore, meticulous parameter adjustment is pivotal for maximizing model efficacy. This study delves into various machine learning parameters, exploring their role in accelerating training times, and enhancing model accuracy. Additionally, optimal optimizer selection strategies for specific machine learning tasks will be examined. Fig. 2 shows the confusion matrix of this proposed model. Table 2 demonstrates how the accuracy is increasing in training time. Fig. 3 describes the Training loss, Validation loss and Accuracy obtained per epoch during training time.

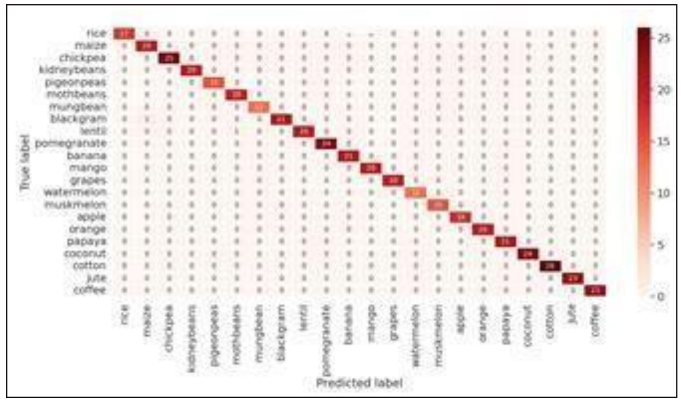

Fig. 2: Confusion Matrix for this Proposed Model

Table 4: Accuracy of the Model Over the Epochs During Training Time

Epoch	Train/L Loss	Metrics/Accur Acy_top1	Metrics/Accura Cy_top5	Val/Loss
1	0.993	0.15294	0.41176	1.9314
2	0.822	0.3451	0.62353	1.8722
31	0.162	0.88627	0.95294	1.5416
32	0.166	0.86667	0.95686	1.5427
55	0.096	0.89412	0.96078	1.5256
56	0.092	0.89412	0.94902	1.5273
99	0.061	0.89412	0.96078	1.5237
100	0.058	0.8902	0.96078	1.5239

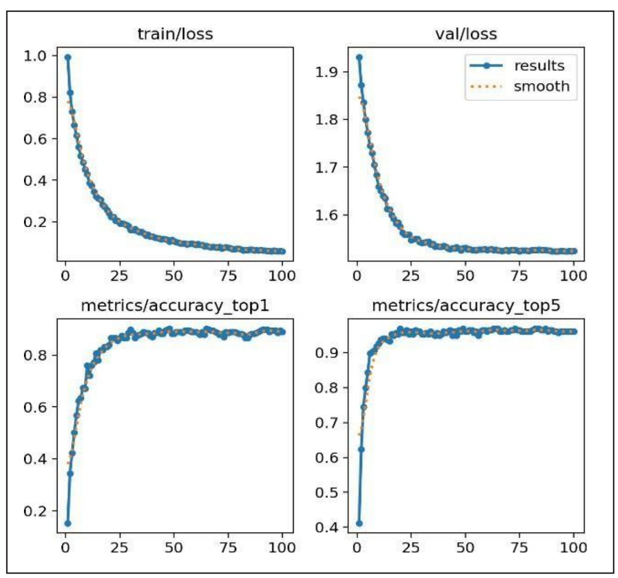

Fig. 3: Training loss, Validation Loss and Accuracy Obtained Per Epoch During Training time

V. CONCLUSION

In this study, a ML-driven Crop Recommendation System using SVM has been experimented for revolutionize agriculture, and empower farmers. Using historical data of different factor that can affect the agriculture and employing SVM classifier this proposed system achieved 96% accuracy. In summary, our Machine Learning Driven Crop Recommendation Model signifies a pivotal shift in agriculture. We aim to redefine decision-making for farmers by integrating cutting-edge technology with inclusivity. This journey towards a more informed, sustainable, and empowered agriculture is just beginning, and we invite every farmer to join us in shaping this transformative future.

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