An Ensemble Method For Crop Recommendation With Weather And Soil Parameters

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Abstract- *India is the world's second largest producer of wheat and rice and world's first producer of several other crops. So, it's not surprising that agriculture rules more than half of India's population economically. The system predict crop based on a combination of ensemble machine learning models with Random forest, K - Nearest Neighbors and Decision tree that includes weather and soil parameters. This automated crop suggestion system alleviates farmers from the pitfalls of traditional farming practices and paves way for better agricultural profit and productivity. Furthermore, it proves to give the best accuracy and present the most accurate result. Thus, the most precise crop to be grown in the farmer's agricultural land is suggested.*

Keywords*-* Precision agriculture, ML, Ensemble method, RF, KNN, DT.

I. INTRODUCTION

Agriculture is one of the most important aspects of the economic growth of India. It has been in the country for 1000 years. As agriculture has grown over the years, traditional techniques have changed with the use of new technologies and equipment. However, some small farmers in India still use old traditional farming methods. This is because there is not enough money to use modern methods. At present, the growth of agriculture is slowing due to lack of smart technologies. Traditionally, 50% of water is wasted, and production is reduced. India is the world's second largest producer of wheat and rice and world's first producer of several other crops. So, it's not surprising that agriculture rules more than half of India's population economically. By taking into account of the undulating nature of the environment and soil parameters that Indian agriculture relies on, farmers don't find the most precise agriculture techniques for better yield. But they are unaware of such influencing parameters. They always prefer to trust their instincts and follow traditional farming methods. Such unsure practices may unfortunately cause the anticipated productivity and profitability become unsubstantial. Since soil is a non-renewable natural resource the soil health and land productivity may deteriorate overtime. This may lead to unpleasant implications on the farmer's life as well as the status of food security in the specific region. In the thought of extenuating this situation, smart farming techniques can be imbibed.

Unfortunately, only a limited portion of the earth's surface is suitable for agriculture uses due to various limitations, like temperature, climate, topography, and soil quality, and even most of the suitable areas are not homogenous. When looking the versatilities of landscapes and plant types, many new differences start to emerge that can be difficult to quantify. Moreover, the available agricultural land is further shaped by political and economic factors, like land and climate patterns and population density, while rapid urbanization is constantly posing threats to the availability of arable land. Over the past decades, the total agriculture land utilized for food production has experienced a decline. In 1991, the total arable area for food production was 19.5 million square miles (39.47% of the world's land area), which was reduced to approximately 18.6 million square miles (37.73% of the world's land area) in 2018 [1]. As such, the gap between demand and supply of food is becoming more significant and alarming with the passage of time.

Further examination showed that every crop field has different characteristics that can be measured separately in terms of both quality and quantity. Critical characteristics, like soil type, nutrient presence, flow of irrigation, pest resistance, etc., define its suitability and capability for a specific crop. In most of situations, the differentiations of characteristics can exist within a single crop field, even if the same crop is being cultivated in entire farm; hence, site-specific analyses are required for optimal yield production. Further, adding the dimension of time, specific crops in the same field rotate season-to-season and biologically reach different stages of their cycle within a year in areas where location and temporal differences result in specific growth requirements to optimize the crop production. To respond to these demands with a range of issues, farmers need new technology-based methods to produce more from less land and with fewer hands.

Considering the standard farming procedures, farmers need to visit the agriculture sites frequently throughout the crop life to have a better idea about the crop conditions. For this, the need of smart agriculture arises, as 70% of farming time is spent monitoring and understanding the crop states instead of doing actual field work [2]. Considering the vastness of the agriculture industry, it incredibly demands for technological and precise solutions with the aim of sustainability while leaving minimum environmental impact. Recent sensing and communication technologies provide a true remote “eye in the field” ability in which farmers can observe happenings in the field without being in the field. Variety of autonomous tractors, harvesters, robotic weeders, drones, and satellites currently complement agriculture equipment. Sensors can be installed and start collecting data in a short time, which is then available online for further analyses nearly immediately. Sensor technology offers crop and site-specific agriculture, as it supports precise data collection of every site. Recently, the Internet-of-Things (IoT) is beginning to impact a wide array of sectors and industries, ranging from manufacturing, health, communications, and energy to the agriculture industry, in order to reduce inefficiencies and improve the performance across all markets [3] [4].

1.1 Precision agriculture

Precision agriculture [6], [7] is one of the solutions to ensure food security for the entire world [8]. Precision agriculture also abbreviated as digital agriculture is a technology enabled data driven sustainable farm management system. It is basically the adoption of modern information technologies, software tools, and smart embedded devices for decision support in agriculture [9] as shown in figure 1.2. Mechanized agriculture and the green revolution are the two key components of the first and second agriculture revolution. Precision farming is an important part of the third agriculture revolution [10].

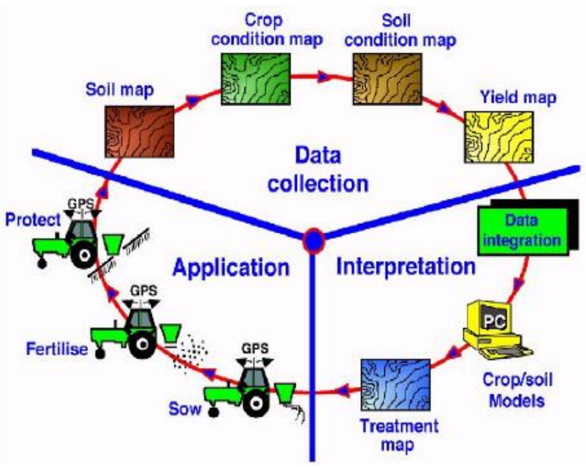

Figure 1.2: Precision Agriculture basic steps.

John Deere introduced this technology in 1990 for the sowing of seeds and spraying of fertilizers using global positioning system (GPS) controlled tractors. The main focus of precision farming is to reduce the production cost and environmental effects to increase the farm's profitability. Digital technologies such as IoT [11], AI, data analytics, cloud computing, and block-chain technology play a key role in precision agriculture. In precision farming, IoT based smart sensors are deployed in the agriculture land for collecting data related to soil nutrients, fertilizers, and water requirements as well as for analysing the crop growth. Autonomous and semi-autonomous devices such as an unmanned aerial vehicle (UAV) [12] and robots are used for identifying weed and disease in the plants using computer vision techniques. Satellite images are also used in precision agriculture for monitoring the field and identifying the diseases in the plants.

The data obtained from the deployed sensors [13] are processed and analyzed using ML algorithms to make farming practice more controlled and optimized. ML algorithms are also used for weather and rainfall prediction based on the data obtained from sensors, climatic records, and satellite images. This could save the lives of thousands of farmers who commit suicide because of crop loss due to uncertainty in weather conditions. Smart livestock management is an important component of precision agriculture. It helps in monitoring the health, welfare, productivity, and reproduction of animals throughout their life cycle. Sensors and cameras monitor animal's health and computer vision techniques help in making intelligent decisions such as stopping the communal spread of diseases. Autonomous tractors and automated irrigation systems provide modern farming solutions to farmers. The widespread utilization of precision farming across the world is due to the presence of innovative machine and deep learning (DL) algorithms, high-speed internet access, and efficient computational devices. In [14] authors have discussed applications of ML for sustainable agriculture supply chain (ASC) performance. Authors have presented a unique ML-ASC framework that can guide researchers and agriculture practitioners to understand the role and importance of digital technologies in the agriculture industry. In [15] authors reviewed different ML applications in agriculture and discussed how digital technologies will benefit the agriculture industry.

1.2 Machine Learning in Crop Prediction

Agriculture industry is globally US$5 trillion industry and now it has been revolutionized with artificial intelligence and IoT technologies These innovative tools are assisting famers to improve crop yield, monitor soil

parameters, livestock health and temperature conditions, control pests and improve other agriculture related tasks.
A Crop Selection Method (CSM) [12] categorizes the crops as annual (crops that can be grown anytime in the whole year), seasonal (crops that can be grown in a specific season), long-term crops (take a long time to grow) and short-term (take a short time to grow) crops. In many tropical and subtropical countries including India, the amount of rain received is indicative of the crop yield that can be expected that year. According to the approach discussed in [15], multiple sequences of crops are possible from the four categories but only the sequence which gives the best mean yield is selected. For the selection of the best sequence of crops, prediction of the yield rate of the crop is imperative and is predicted based on features like water density, weather, soil type, crop type. Using the predicted yields of the crop multiple sequences may be possible, and they can be filtered out the best sequence by using the ensemble model or multi-learner model.

Conventional ML models such as SVM, RF finds difficult to accurately estimate soil parameters and weather conditions in varying ecosystem. Therefore, Ensemble, robust and adaptive ML algorithms such as SVMRF, and other ensemble algorithms can be explored to effectively forecast different parameters in precision agriculture. In large agriculture fields autonomous system can be built for crop health and growth monitoring using ML and artificial intelligence.

Machine Learning is a computer science field where new developments have recently been developed, which also helps to automate assessment and processing carried out by mankind so that human manual power is reduced. Machine learning is a type of artificial intelligence (AI) that enables computers to learn without explicitly programming, according to the technological goal. Machine learning focuses on computer program, which can change if new data are exposed. It is difficult for novice farmers to find the right crops based on the appearance of the soil. Agricultural decline must also be prevented.

Most of the ensemble methods ensure good accuracy and incorporating big data analysis and data mining can be beneficial for a large scale system. What we require is a method to collect data efficiently since temperature and rainfall have a huge impact on yield; we also require a robust system that can predict the weather accurately. Need a special focus on soil properties and nutrients as they are the major factors for crop recommendation.

II. RELATED WORK

2.1 Soil Properties and Weather Prediction

Prediction of soil properties is the first and the most crucial step which influences the selection of crop, land preparation, selection of seed, crop yield, and selection of fertilizers/manure. The soil properties are directly related to the geographic and climatic conditions of the land in use and hence are an important factor to take into consideration. The soil properties prediction mostly consists of predicting nutrients in the soil, soil surface humidity, weather conditions during the lifecycle of the crop. Human activities have highly affected the properties of soil and hence our ability to cultivate the crops [16]. In general, there are 17 essential elements as listed in table 3 which play an important role in plant growth. The growth of crops depends on the nutrients available in a particular soil.

Depending on the nutrients farmers make informed decisions as to which crop is optimal for the land. However, the nutrients can be added through fertilizers, manure, etc. but with an additional cost. Some of them may also damage the environment and have an adverse effect on the soil cycle. A scientific analysis of soil nutrients, soil moisture, pH is important for determining the soil properties. Acar *et al.* [17] employed an extreme learning machine (ELM) based regression model for prediction of soil surface humidity. The author selected two terrains having area 4 KM2 and 16 KM2 located in Dicle university campus for experimental analysis. The real-time field data was extracted using polarimetric Radarsat-2 data, which was pre-processed using the SNAP toolbox and features were added with the help of local measurements by separating the field into square grids. Once the pre-processing and feature extraction is done the data is passed to ELM based regression model to predict the soil surface humidity. The algorithm was tested with 5 different kernel functions and the prediction was validated using leave-one-out cross-validation technique. The experimental results confirmed the lowest root mean square error (RMSE) of 2.19% when using `sine' kernel function.

Wang *et al.* [18] deployed soft sensors based on ELM for the measurement of nutrient solution composition in the soilless cultivation method. The soilless cultivation method is an emerging planting method. It is imperative to monitor the pH value, temperature and concentration changes in nutrient solution composition as the performance of soilless cultivation is highly dependent on these parameters. These auxiliary measurements are fed to a deep belief network-based ELM which predicts the values of significant variables.

Reda *et al.* [19] explored ML algorithms to estimate soil organic carbon (SOC) and total nitrogen (TN) in soil samples collected from four agricultural lands of Moroccan. Dataset of near-infrared spectroscopy is utilized in comparison to traditional chemical methods as this technique reduces the computation time and resource utilization. The ensemble learning modeling algorithm presents the best performance among other regression models and back-propagation neural networks (BPNN) algorithm. The proposed algorithm presents $R2$ of 0.96, RMSE of 1.92, performance to deviation (RPD) of 4.87 for SOC and $R2$ of 0.94 and RMSE of 0.57, RPD of 4.91 for TN prediction.

2.2. Crop Yield Prediction

A significant piece of information for any farmer is the prediction of crop yield and how the yield can be increased. pH value, soil type, and quality, weather pattern: temperature, rainfall, humidity, sunshine hours, fertilizers, and harvesting schedules are some of the parameters which play an important role in predicting the crop yield [20]. Scientifically manual farming can be considered as a feedback control system in which the corrective action is taken once a setback in a crop is observed. The crop yield will highly depend on the efficiency of the optimal utilization of the above-mentioned resources. If some kind of anomaly goes undetected in the initial stage may harm the crop yield in an unprecedented way. Singh *et al.* [21] assessed hailstorms on India's wheat production and observe that in February and March 2015 alone the hailstorm events caused a decline of 8.4% in national wheat production. For financially weak farmers in a country such as India, where intermittent storage of harvested crops is a rare resource, accurate weather predictions may turn to be miraculous for farmers. ML models when systematically applied to a system act as feedforward control. With the help of accurate ML models, we can anticipate the factors which are going to affect the crop yield. Hence the corrective action can be taken before even an anomaly hits the crop production.

Kamir *et al.* [22] used ML models to identify the yield gap hotspots in wheat production. Authors generated very high-resolution yield maps using data from various sources between 2009 and 2015. The data was collected from various sources:

(a) NDVI time-series data across Australia using the MOD13Q1 data set,
(b) Rainfall and temperature data were collected from historic climate data at Australia bureau of metrology,
(c) Maps for observed grain yield were collected at source using intelligent harvesting machines.

The dataset generated were tested with 9 ML algorithms: RF, XGBoost, Cubist, MLP, SVR, Gaussian Process, k-NN, and Multivariate Adaptive Regression Splines. The authors combined predictions from each of the algorithms into ensembles for prediction optimization. Out of these algorithms, SVR with RBFNN outperformed other algorithms and investigators were able to achieve the yield estimate with an R2 of 0:77 and an RMSE value of 0:55 than 1. The results were validated using 10-fold cross-validation techniques applied to the full data set.

The data was fed to advanced regression algorithms:

(a) Gaussian Process Regression,
(b) SVR,
(c) Boosted Regression tree
(d) RF Regression models and the prediction form each of the regression models were compared and evaluated.

RGB dataset obtained from cameras installed in UAV is used to train the six-layer CNN. RGB dataset best predicts the crop yield in CNN with MAE of 484.3.

Koirala *et al.* reviewed deep learning approaches for fruit detection and yield estimation. CNN in the context of computer vision is widely used for feature extraction from images that provide useful insight to object detection and yield estimation. Peng *et al.* explored remote sensed satellite-based Solar-Induced Chlorophyll Fluorescence (SIF) dataset for training ML algorithms to predict maize and soybean yield in the mid-west region of the United States. Simulation results show that non-linear algorithms such as SVM, ANN, RF best predict the crop yield in comparison to least absolute shrinkage and selection operator regression (LASSO) and ridge regression (RIDGE) algorithm. Khaki and Wang predicted the hybrid maize yield with a dataset of 2,267 locations of the United States and Canada between the years 2008 to 2016 using deep neural networks (DNN). Genotype, weather, and soil properties were the three components used to train DNN. The proposed model accurately predicts the maize yield with RMSE of 12% of the average yield for predicted weather dataset and 11% of the average yield for perfect weather dataset and outperforms LASSO, shallow neural network (SNN) and regression tree (RT). Simulation results shows that environmental factors have a large impact on the prediction accuracy of crop yield. In most areas of Africa, agriculture field data is scarcely available thus remotely sensed dataset is widely used for monitoring the field.

More and more researchers have begun to identify this problem in Indian agriculture and are increasingly dedicating their time and efforts to help alleviate the issue. In

[21], the authors make use of Regularized Greedy Forest to determine an appropriate crop sequence at a given time stamp. The authors of have proposed a model that makes use of historical records of meteorological data as training set. Model is trained to identify weather conditions that are deterrent for the production of apples. It then efficiently predicts the yield of apples on the basis of monthly weather patterns. The effect of temperature on the sugar content of apples is also taken into account to detect potential amount of damaged yield. The use of several algorithms like Artificial Neural Network, K-Nearest Neighbors, and Regularized Greedy Forest is demonstrated in [18] to select a crop based on the prediction yield rate, which, in turn, is influenced by multiple parameters. Additional features included in the system are pesticide prediction and online trading based on agricultural commodities. Another intelligent model, presented in [20], allows for the prediction of soil attributes such as phosphorous content. Here, the authors make use of different classification techniques like Naive Bayes, C4.5, Linear Regression and Least Median Square to achieve high prediction accuracy. This system can be very beneficial for farmers to determine the suitability of the soil to support a particular crop.

III. PROPOSED WORK

Our Firstly, data is collected from Soil Survey department of any state agriculture ministry or global sources. The data collected is then one hot encoded to convert categorical variables into numeric variables. After pre-processing, feature scaling is a method used to normalize data in each attribute. This is mainly used to keep all attributes in the same value range to avoid giving higher priority to attributes with higher values, than data is normalized to give equal priority to all the attributes. It is then provided as input to the proposed machine learning model for training. The proposed machine learning model is a weighted ensemble machine learning model. Then training of the proposed model is performed. User input is supplied to the trained model and the output is collected. The recommended crop is then presented as the output.

Proposed system is developed with weighted ensemble learning model. Ensemble learning technique in machine learning integrates multiple models to achieve increased performance. It combines the power of multiple ML algorithms so that one model can correct the errors of another and predict results with much higher accuracy. Two or more models can be used as the base learners in this technique. The base learners should be chosen such that each of them performs well individually so that the combined model gives better results.

The proposed system uses k-Nearest Neighbours, Decision Tree and Random Forest as our base learners for the Majority Voting technique. Majority Voting is an ensemble technique that is one of the best models to solve classification problems. In this, the training set is supplied to all the models and each of them gets trained individually. The inputs for prediction are then fed to all the models separately. Each prediction result is counted as a vote and the output with the maximum number of votes is given as the final result.

4.2 Proposed Model

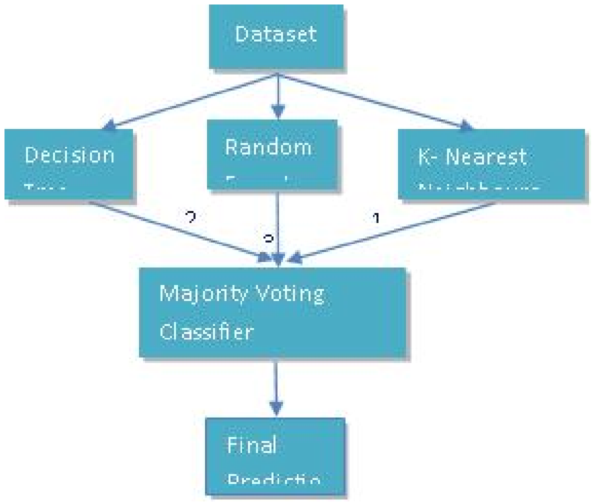

Figure 4.2: Proposed models.

Figure 4.2 shows the working of the proposed system. Weighted ensemble technique is used with Decision Tree having weight 2, Random Forest having weight 3 and K-Nearest Neighbour having weight 1.

Random Forest, Decision Tree and kNN are combined to build the majority voting ensemble model to recommend the most suitable crop. Here, each model is first defined. Information gain is used as the criteria to decide the attributes at each level of the decision tree. In Random Forest, 10 decision trees are constructed and combined to predict the result. Euclidean distance (p=2) is considered to determine 26 nearest neighbours in kNN whose output value determine the predicted crop. These results are combined with weights 2, 3, 1 for Decision Tree, Random Forest and kNN respectively to give the final predicted crop of the machine learning system.

4.3 Learner Used in Proposed Model

4.3.1 Decision Tree

General working is as follows:

1. Start the tree with root node S (complete dataset)
2. Find the best attribute using Attribute Selection Measure, Information Gain.The categorical feature that will maximize the information gain value using the impurity criterion entropy is chosen at each level.

Entropy (T) = $\sum_{i=0}^{n} - f_i \log(f_i)$

n – number of unique values of the target variable

f_i – probability of i^{th} value of target variable

Gain (T, X) = Entropy (T) — Entropy (T, X)

T = target variable

X = Feature to be split on

Entropy (T, X) = the entropy calculated after the data is split on feature X

3. Divide S into subsets
4. Generate decision tree node (which contains the best attributes)
5. Recursively continue from step 3

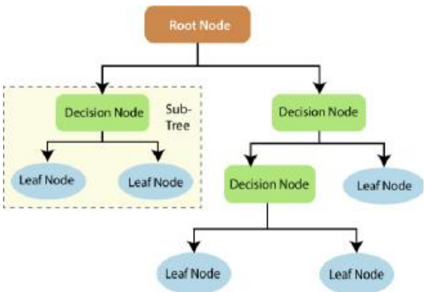

Figure 4.3: Structure of Decision Tree.

Figure 4.3 shows the branches and internal node structure of the decision tree. The branches are the unique categories of the attributes and the leaves indicate the attribute name.

4.3.2 Random Forest

General working is shown below:

1. Number of decision trees to be constructed is chosen as N.
2. Any random subset of the training set is considered to construct each decision tree.
3. The decision trees for the selected data points is constructed in a similar way using information gain as attribute selection measure.
4. Repeat steps 2 and 3 for N times.
5. The category of decision trees that wins the majority votes in the predictions will be assigned for the new data points.

IV. RESULTS WORK

The Table 6.1 Comparison of Existing and Proposed Model.

Models	Existing Method Accuracy	Proposed Model Accuracy
Decision Tree	**80.74% [56]**	**86.94%**
KNN	**NA**	**66.52%**
Random Forest	**84.17% [56]**	**86.69 %**
SVM	**81.11%[59]**	**82.81%**
Our Model	**--**	**87.55 %**

From the above result we can conclude that our model performs better than existing models. The Chart is shown below:

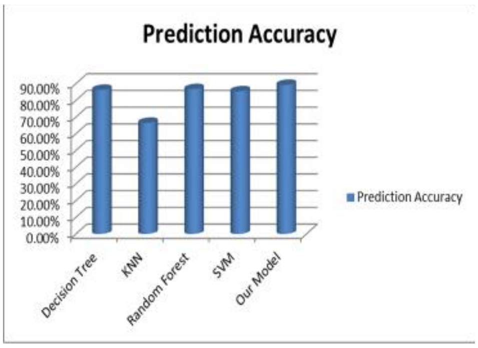

Figure 6.6: Chart representing accuracy of various models.

This thesis proposed a model that will plays a major role in assisting the farmers to make a decision on the best crop to be grown on their farm land located depending on their location and environment. This system considers various soil and environmental factors, and IoT sensor values to predict the accurate crop. The proposed model provides an advantage by combining the accuracies of KNN, random forest and decision tree algorithms and gives a resulting accuracy which is higher than the accuracy of the existing techniques.

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