Chapter 10
AI-Enabled Crop Recommendation System Based on Soil and Weather Patterns

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ABSTRACT

Agriculture is the foremost factor which is important for the survival of human beings. Farming contributes to a very big part of GDP; still, several areas exist where improvements are required. One of those is crop recommendation. Crop productivity is boosted as a result of accurate crop prediction. As crop production has already started to suffer from climate change, improving crop output is consequently desirable because agronomists are impotent to select the appropriate crop(s) depending on environmental and soil parameters, and the mechanism of forecasting the selection of the appropriate crops manually has failed. Factors like soil characteristics, soil types, climate characteristics, temperature, rainfall, area, humidity, geographic location etc. affect crop forecast. This chapter focuses mainly on building a recommendation system, i.e., suggesting the kind of the crop by applying various machine learning and deep learning techniques depending upon several parameters. The system would help the farmers for the appropriate decision to be taken regarding the crop type.

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INTRODUCTION

Agriculture is the cornerstone of the nation's development. Due to its extraordinary agricultural areas and other resources, India is known as an agricultural country. Elements like temperature and soil moisture have an impact on how productive, contagious, and yield-producing agriculture has grown recently (Edwin, 2017). Agriculture-related issues have impeded the country's progress. It is vital to modernize the recognized farming practices nowadays. New agricultural trends are required to manage crops in a regulated atmosphere.

The choice of a crop is one of the most crucial elements that directly affects the final output; as a result, a farmer should always choose the best crop choice while taking environmental factors into account. Choosing the optimum crop for a specific farm can be difficult because there are so many different variables that could influence the yield. Although crop suggestions from specialists are frequently requested, many farms cannot afford or have access to this option due to its time and expense requirements. It has seen a huge increase due to their immense benefits in supporting users' needs by locating the most appropriate items based on information extracted from a collection of data.

The use of recommender systems in agricultural management has recently produced some intriguing and promising results. Similar to the Amazon shop, these technologies are essential in guiding users' actions by helping them increase profits or reduce risks. Recommender Systems are used for a variety of purposes in many modern digital enterprises like Yahoo, Google, Netflix etc. including consumer segmentation, fraud detection, financial banking, healthcare systems, and education (Iniyan et al., 2023).

Recommendation Systems are utilized to assist farmers in making wiser decisions. The crop recommendation discipline does not, however, have a comprehensive classification strategy for its algorithms and features. The lack of a systematic literature review that is explicitly focused on this issue and the diversity of techniques presented in the surveys are the main reasons behind this, as the majority of studies have only looked at the application of machine learning to agricultural yield prediction (Yamparla, 2022). As a result, choosing an algorithm and input parameters that meet one's needs can be difficult and confusing while developing a crop recommender system. Also, it would be challenging for academics to keep track of agricultural advancements and algorithm usage.

The motivation behind this research is to create a system that can advise which crop should be grown in a specific circumstance. Based on the levels of nitrogen, phosphorus, and other elements in the atmosphere, it makes forecasts (Sharma and Rathi, 2016). It chooses which crop to grow by measuring the amount of rainfall and other weather factors. Also, it offers predictions depending on the soil's current state. The initiative teaches farmers and the general public which crops may be produced in a specific area using a range of machine learning techniques. Both the agriculture business and general use can benefit from this effort.

The structure of this chapter is as follows: A comprehensive overview of crop recommendation systems is provided in Section 1. Review of the literature is presented in Section 2. Section 3 discusses the suggested work and dataset aspects. An examination of the outcomes is covered in Section 4. We wrap up the work in section 5 with a few potential future developments.

LITERATURE REVIEW

(Van et al., 2020) conducted a systematic literature assessment. The analysis shows that soil type, temperature and rainfall are the most frequently utilized features, while ANN`s are the most frequently used algorithm in this model. (Rashid et al., 2021) reviewed various ML algorithms for predicting the agricultural yield with extra special importance on palm oil yields. (Kalimuthu et al., 2020) have used an approach where Naive Bayes algorithm is used. (Sharma et al., 2021) have given a comprehensive evaluation of ML applications in the realm of agriculture. By identifying and diagnosing eating disorders, reproductive patterns, or behaviour prediction, machine learning with computer vision can be utilised to increase livestock productivity.

In order to create a pre-season, (Cunha et al., 2018) did a forecast of soybean/maize production without using NDVI data, a system is built that integrate satellite-derived statistics on soil parameters, physical model-based seasonal climate forecasting data, precipitation and other sources. (Pande et al., 2021) developed a practical and user-friendly yield prediction system using ML algorithms to estimate the crop yield and make recommendations on fertilisers to increase yield. Authors presented a practical and user-friendly yield prediction system (Reddy and Kumar, 2021). The most profitable crop list can be picked using machine learning algorithms, and they can also forecast crop yields for user-selected crops. Selected Machine Learning techniques like SVM, ANN, RF, Multivariate Linear Regression, and k-NN are used to predict crop yield. The research examined CYP using ML techniques (Tahaseen and Moparthi, 2021) that were distinct from the features that were selected based on the crop attributes, scale and geological position these decisions were largely influenced by the availability of the data set. ML techniques were used to estimate crop yields while taking into account variables like temperature and weather.

Various machine learning techniques are covered for weed and pest detection, crop production prediction, and plant leaf disease detection. (Sharma et al., 2021) discussed the current situation of agricultural yield around the world is followed by a quick introduction to widely used characteristics and forecasting techniques. ML and AI can be used to increase agricultural production in India to meet public demand. (Ray et al., 2022) proposed 22 types of crops using distribution analysis, correlation analysis, majority voting and ensembling, with accuracy of 99.54% and 98.52%. (Vashisht et al., 2022) proposed an extreme learning machine to predict rice crop yield based on geography, season, and cultivation area. (Gupta et al., 2022) demonstrated that ML algorithms can be used to segment large amounts of data to make crop yield predictions.

(Seireg et al., 2022) used cascading regression and stacking regression to predict wild blueberry yield with accuracy. (Rasheed et al., 2021) tested a decision-aiding tool on historical data of cultivated land segments in Pakistan to estimate net profit and predicted production. The process of using machine learning techniques to train a model for seeing trends in data and then using that model to predict crops are defined by (Pant et al., 2021). Predictive analytics was used by (Chandraprabha et al., 2021) to forecast soil nutrients for various crops using Tamilnadu's soil-based dataset. (Raja et al., 2022) presented classification and feature selection techniques to estimate plant cultivation yields, with an ensemble technique outperforming existing classification techniques in prediction accuracy.

For the purpose of forecasting annual crop yields in West Africa, (Cedric et al., 2022) presented a machine learning-based prediction method based on machine learning to predict annual crop yields in West Africa, using Decision Tree, multivariate logistic regression, and k-NN. (Ali et al., 2022) evaluated crop production using remote sensing techniques and direct empirical statistical models. (Pantazi et al., 2016) used an unsupervised learning algorithm to predict wheat yield using satellite imagery and soil data. Using ML regression approaches for Time-Series Imagery of Landsat 8 OLI, (Aghighi et al., 2018) performed the prediction of silage maize. Modified recursive feature elimination (MRFE), a unique feature selection technique is defined to choose the most pertinent features from a crop prediction dataset (Mariammal et al., 2021). The performance analysis justifies why the MRFE technique outperforms other FS methods with a 95% accuracy.

Three important steps: pre-processing the dataset, EDA and detection module are included (Kumar et al., 2021) and plant disease prediction has been done. More than 98% of predictions for each disease turned out to be accurate on average. This research establishes the viability of employing this method for less expensively and more quickly identifying plant diseases. APSIM crop model and Daily high-resolution CubeSat photos are combined by (Ziliani et al., 2022). APSIM and CubeSat photos combined to produce high-resolution yield maps, with $R^2 = 0.73$ and RMSE = 12%.

(Vlachopoulos et al., 2022) found that the best algorithm for GAI prediction was the random forests algorithm, with an MAE of 0.67 and RMSE of 10.86%. Yield maps created using various Kriging techniques and other mapping approaches (Birrell et al., 1996) showed the same broad patterns, but localised yield features were represented differently.

(Goel and Mishra, 2022) reported 95.64% accuracy using phenological data and deep learning algorithms. On the basis of input dimensions, the deep recurrent Q-learning network creates an environment for agricultural yield prediction, as mentioned by (Elavarasan and Vincent, 2020). Q-Network is a better option to forecast crop yield, with 93.7% accuracy. ANN method tested by (Haque et al., 2020) to show how different factors affect crop yield, with MSE and standard deviation used to illustrate error rate. (Cunha and Silva, 2020) created a productive crop yield model using crop calendars, weather forecast information, and remote sensing data. (Mondal and Banerjee, 2021) developed a model that incorporates rainfall, temperature, and chemical elements to calculate agricultural productivity. The results show that the proposed model performs fairly well. (Bose et al., 2016) developed Spiking Neural Networks for distant sensing spatiotemporal analysis of picture time series to estimate crop yield, with an average accuracy of 95.64% and an average error of 0.236 t/ha.

(Saeed and Lizhi et al., 2019) developed a DNN approach to improve prediction accuracy, reducing average yield to 11% and 46%. A multilayer deep learning model combines RNN and CNN to extract spatial and temporal features from soil property data, time-series remote sensing data, and model outputs (Sun et al., 2020). SSTNN is a novel deep learning architecture, developed by (Qiao et al., 2021) that combines recurrent neural networks and 3D convolutional neural networks to extract temporal relationships from multi-spectral images. Multi-parametric Multiple Kernel DNN (MMKDNN) by (Kalaiarasi and Anbarasi, 2022) enhanced learning capacity of MDNN to improve agricultural yield prediction for medium-scale data.

(Abbaszadeh et al., 2022) integrate the outputs of many deep neural networks, such as the 3DCNN and ConvLSTM, to produce more reliable and accurate soybean crop production estimates. The result is a probabilistic estimate of soybean crop yield. CNNs and hyperspectral imaging were used to model the spectrum data set and compare the impacts of PCA and multidimensional scattering correction (Pang et al., 2020). (Alebele et al., 2021) represented rice yield estimation based on Gaussian kernel regression that outperforms Bayesian linear inference and probabilistic Gaussian regression with higher prediction accuracy.

(Martinez et al., 2021) proposed Gaussian processes (GPs) that enable the identification of climate extremes, anomalies, and their associated causes that affect crop productivity. (Qiao et al., 2021) developed a 3-D convolutional neural multi-kernel network to capture hierarchical features for agricultural yield prediction. (Sivanantham et al., 2022) found that using orthogonal basis functions and quantile regression improved prediction accuracy and precision by 32% and 9%, respectively.

(Li et al., 2022) concentrated on the integration of a variety of solar-induced fluorescence (SIF), satellite data, land surface temperature (LST), and microwave vegetation optical depth (VOD), including optical-based vegetation indices with environmental data (soil, climate, topography and geography). Machine learning techniques outperformed linear regression techniques to predict maize, rice, and soybean yields when combined with satellite data and environmental data. (Gupta et al., 2021) hope to assist farmers in increasing the yield of their crops by gathering and analysing data on soil, temperature, wind speed, rainfall, crop productivity, seed and humidity (in some places). The MapReduce architecture is used to process and analyse data, and K-means clustering is used to predict crops.

(Liu et al., 2022) used MLR to predict the occurrence of plant diseases using IoT-based environmental parameters, with up to 91% accuracy. (Udutalapally et al., 2021) trained CNN to create an illness prediction system with 99.24% accuracy. (Makkithaya and G., 2022) trained deep residual network-based regression models ResNet-16 and ResNet-28 for soybean production prediction using federated averaging. (Mehta et al., 2021) evaluated the effectiveness of various crop yield prediction algorithms, including CNN, LSTM, and the CNN-LSTM framework. (Agarwal and Tarar, 2021) improved their model by using deep learning and machine learning to forecast an appropriate yield, with 97% accuracy. According to the analysis done by (Bodapati et al., 2022), data was first sorted using an artificial neural network technique, and harvest production was then predictably calculated using machine learning. During the testing phase, the yield value is roughly estimated based on specific restrictions.

(Mopidevi et al., 2022) have used machine learning and deep learning to predict Ficus stem benjamina stem in controlled areas. Comparative studies that evaluate crop development using ML techniques like SVR and RFR are described (Swarnakantha et al., 2022). This article introduces a platform where growers may connect with other growers and specialists through an agricultural forum, as well as sell their crops to domestic and worldwide buyers. (Bhansali et al., 2022) created a recommendation model using N-K-P, Ph.D. value, and rainfall as training parameters to identify type of disease and suggest how to treat or prevent it. (Nancy et al., 2022) have performed an Image based plant disease detection along with classification using ML & DL.

PROPOSED WORK

Building an intelligent machine learning model in Python is the task done here. It suggests the optimum crop to plant depending on the soil's composition, pH level, rainfall, and location. By examining variables such as district, state, season, and crop type using various supervised machine learning approaches, the model focuses on anticipating the agricultural production. The main goal of this method is to give farmers crop recommendations that will assist them choose a crop that will yield more profitably by letting them know the crop yield in advance.

The proposed system stores the information relevant for processing through the ML Algorithms. This module mainly focuses on the testing & training the models with the dataset which is prepared in the staring module and also to make those algorithms ready for prediction. All models are created, then their accuracy and their validation scores are checked and all the models are saved in pkl files for further use for predictions. Also, different outputs are predicted and its accuracy is checked through different - different types of inputs.

Dataset Preparation

We were able to develop a predictive model using the dataset collected from kaggle.com, which will recommend the best crops to plant on a particular farm based on a number of variables. The dataset dimension is (2200, 8). The ingredients present in soil are: Nitrogen, Phosphorous, Potassium.

Data fields:

N - Nitrogen ratio in soil
P - Phosphorous ratio in soil
K - Potassium ratio in soil
temperature - temperature in degree Celsius
humidity - relative humidity in %
pH - soil's pH value
rainfall –rainfall in mm

Figure 1. Dataset snapshot

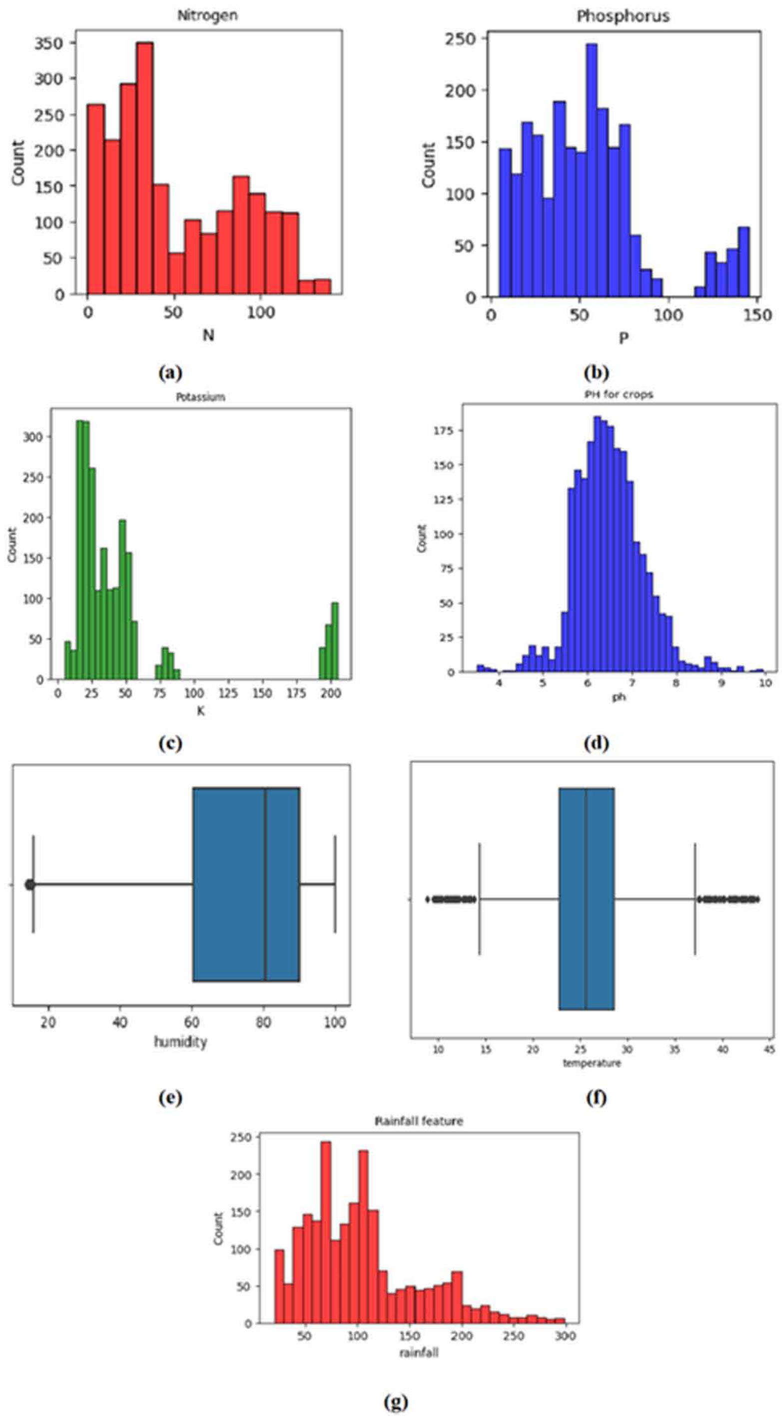
In [5]:
```
crop_df = pd.read_csv('Dataset.csv')
crop_df.head(10)
```

Out[5]:

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
5	69	37	42	23.058049	83.370118	7.073454	251.055000	rice
6	69	55	38	22.708838	82.639414	5.700806	271.324860	rice
7	94	53	40	20.277744	82.894086	5.718627	241.974195	rice
8	89	54	38	24.515881	83.535216	6.685346	230.446236	rice
9	68	58	38	23.223974	83.033227	6.336254	221.209196	rice

Figure 2 shows the illustration of various features of the dataset: (a) Nitrogen (b) Phosphorus (c) Potassium (d) PH (e) Humidity (f) Temperature (g) Rainfall

Figure 2. Features of dataset



Technologies to be Used

Various technologies are used in making of this project. It includes Numpy, Pandas, Matplotlib etc. Also, pytorch and various python libraries are used. In this project, python files, .pynb files and .pkl files are used for model preparation. Also, various ML technologies are used. To run a ML Algorithm on a prepared dataset, various techniques are used to do this.

ML Algorithm Preparation

The algorithms are chosen appropriately and trained and tested with the dataset and many different models are created. The system is an intranet-based system so users can predict crops based on their input values that provides detail general information about the which crop to grow and in which condition. It enhances the agriculture management in adding, viewing and updating the crops that can be grown in a particular area according to the particular condition.

Users may theoretically have access to a large range of products within a specific site. One or more Web pages may serve as tangible representations of these objects. Conceptually, each of these objects represents a distinct kind of semantic entity. During a session on this website, a user may access several of these things at once. Figure 3 shows the approach used in the work done.

The algorithms applied on the dataset mentioned are: Decision Tree, Naïve Bayes Classifier, Random Forest, k-NN. SVM, XGBoost and Logistic Regression. The behaviour and performance of each model is shown in the result section.

Figure 4 represents confusion matrices for various models: (a) Decision Tree (b) Naïve Bayes Classifier (c) Logistic Regression (d) Random Forest (e) Support Vector Machine (f) XGBoost (g) k-NN

RESULTS

All the algorithms are tested and trained on that dataset and different models are created by taking predictions through this model. The algorithm which has to be chosen should work properly with the prepared datasets. So, all the algorithms are trained and tested with the dataset and many different models are created. After checking all those algorithms, the ML Algorithms has to be coded and then models are created so that the proper predictions can be made. Out of the 7 algorithms applied, Naïve Bayes, XGBoost gives the maximum and equal accuracy i.e. 99.55%. Next, Random Forest and SVM give an accuracy percentage of 99.31. k-NN and Logistics regression results into the accuracy values of 98.86 and 98.63 respectively. Decision tree performed the worst in given scenario by providing the accuracy of 85.91% only.

CONCLUSION

The process for proposing crops before cultivation is described in the article. The input data is first preprocessed in order to identify missing values, eliminate redundant information, standardize the data, and convert target attributes into factor attributes. The dataset is divided into training and testing phases before ML techniques are used to the enhanced attributes. To determine the type of crop that is most suitable for growing in a specific plot of land depending on the soil properties (i.e. ratio of nitrogen, phosphorus, and potassium), weather conditions, temperature, soil PH, rainfall, etc., various machine learning algorithms are trained using unknown samples from the training dataset. The testing dataset is used to use the learned classifier to forecast the crop that will be grown. A suitable crop is chosen, and the results are accurately evaluated. The study concludes that XGBoost and Naive Bayes classifiers have the highest accuracy and are the most efficient and appropriate approaches.

Figure 3. Flow chart of the proposed approach

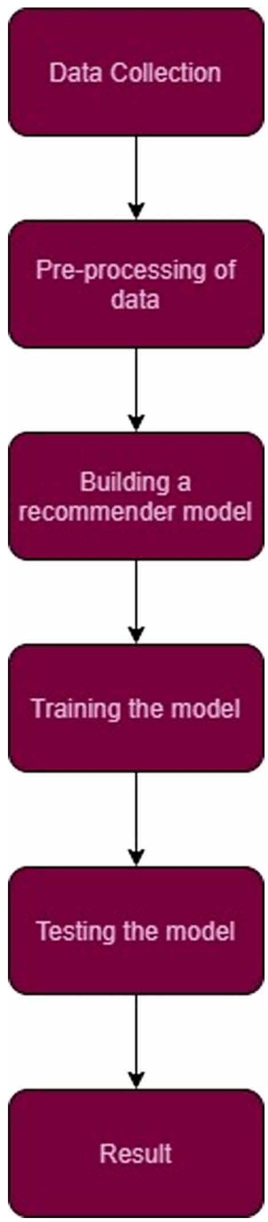


Figure 4. Confusion matrices of various models

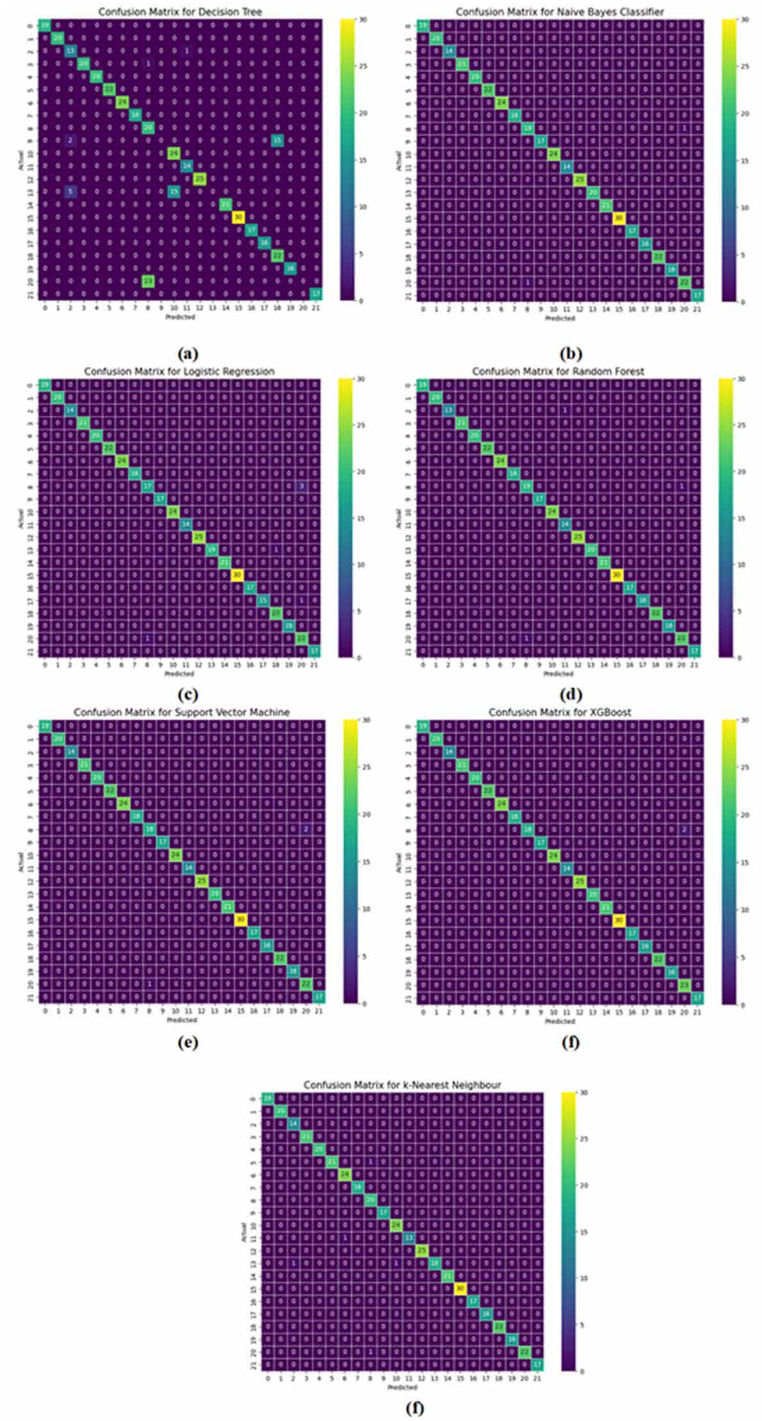
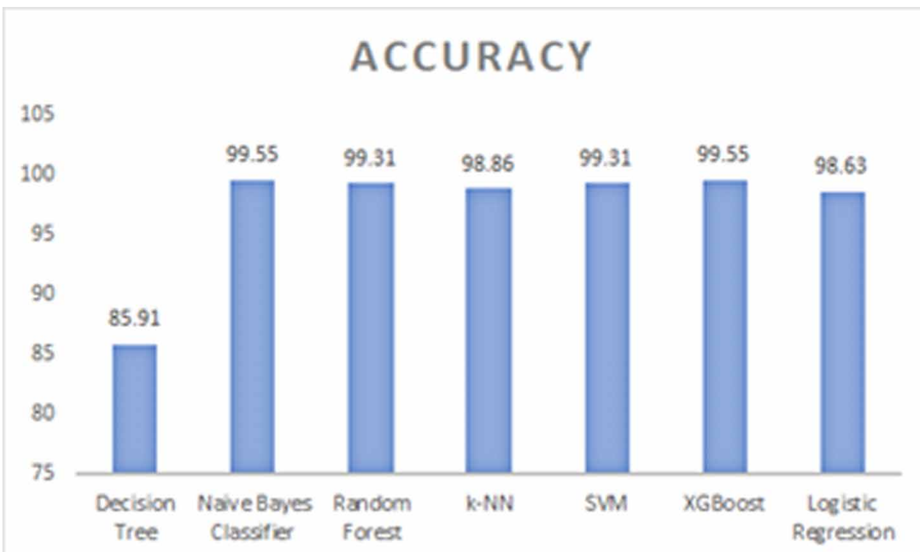


Table 1. Accuracy of various models applied

S. No.	Model	Accuracy (in Percentage)
1	Decision Tree	85.91
2	Naive Bayes Classifier	99.55
3	Random Forest	99.31
4	k-NN	98.86
5	SVM	99.31
6	XGBoost	99.55
7	Logistic Regression	98.63

Figure 5. Accuracy comparison



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