Integrating Soil Nutrients and Location Weather Variables for Crop Yield Prediction

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Abstract:- **This study is described as a recommendation system that utilize data from Agricultural development program (ADP) Kogi State chapters of Nigeria and employs machine learning approach to recommend suitable crops to be planted according to input soil and climate statistics. The purpose of this study is to forecast agricultural production using machine learning techniques. The inferred classifier models here incorporate information from Random forest classifier,Gradient boost and Keras Regressor with Gradient boost exhibiting the greatest accuracy of 98.9%. Forecasts made by machine learning algorithms can now assist farmers in choosing which plant to cultivate based on key variables, including temperature, rainfall, and pH and soil nutrients as nitrogen, phosphorous and potassium. Therefore, this strategy lessens the financial losses that farmers experience when they decide to plant the improper crops. It also helps farmers in their search for new crop varieties that are suitable for cultivation in their region.**

Keywords:- *Machine Learning, Crop Yield, Cultivation, Forecasting, Plantation, Data Mining, Agriculture.*

I. INTRODUCTION

The amount of crops produced per unit of land is referred to as crop yield. yielded agricultural produce (yield of a crop). It is a popular unit of measurement for grains, legumes, and cereals, and it is expressed in pounds, bushels, or per acre, tons. Crop output is a critical aspect in determining agriculture's long-term viability. Environmental factors have a significant impact on crop productivity. Weather has an effect on crop growth and development, which in turn affects intra-season production variability. Variability in agricultural yield is a result of the interaction between space weather and soil quality. (Prasad, 2020). In developing countries, yield of crop monitoring consists mostly of two main types of sample surveys: Early crop productivity predictions are based on subjective surveys, which include producer comments and field inspectors' visual assessment. Later crop yield estimates are based on empirical surveys like whole-plot harvesting or crop cut measurements from sampling farms. (Zhou, 2021). Crop production forecasting is one of the most challenging problems in smart agriculture, and various models have already been proposed and proven thus far. As a result of the fact that a variety of factors, including seed type, climate, fertilizer use, weather, and soil. This difficulty calls for the use of numerous datasets, which shows that estimating agricultural yields is not a straightforward process but rather involves a number of intricate steps. Although more yield prediction accuracy is still preferred, crop yield prediction technologies may now fairly approximate the actual yield. (Klompenburg et al., 2020).

To increase prediction performance, environmental variables such as precipitation, temperature, soil moisture, and solar radiation must be used in agricultural yield estimating models. Recent techniques are introducing non-parametric regression models consisting of highly effective machine algorithms and data mining techniques such as random forest algorithms (Sakamoto, 2020). In addition, Non-parametric probability-based methods for Machine Learning challenges especially for classification and regression tasks have been introduced when predicting yield. (Martinez-Ferrer et al; 2020). Wherever a dataset is accessible, data mining methods, a well-versed computing field, can be used.

This research therefore focuses on developing a model to analyze the vast amount of data from a real-world farm. The system would learn from the gathered data set. So, the Soil nutrients and weather integration model to forecast harvest is a recommender which is an interactive and user-friendly model that is capable of supporting decision makers in Crop Agriculture organizations like ADP, FADAMA, etc., to make decisions with much speed, greater accuracy, and high precision.

II. LITERATURE

Crop yield predictions are made using a variety of machine learning techniques. Terungwa et al., (2020) constructed a model which can forecast crop productivity based on historical data and provides farmers with recommendations for the proper soil nutritional needs to improve crop yield. The XGBoost algorithm was used to forecast crop yields, while the Support Vector Machine method was utilized to make recommendations for improving soil nutritional needs. The accuracy of the prediction using XGBoost was 95.28%, whereas the accuracy of the fertilizer suggestion using SVM was 97.86%. Zhou (2021), estimated rice and wheat province of Punjab, Pakistan, yields by combining the highest. By using Machine Learning Regression (MLR) models, the Enhanced

ISSN No:-2456-2165

Vegetation Index (EVI) can be measured throughout the crop-growing season. To compare the predicted accuracy of five MLR models, a fivefold cross-validation method was used. The regression model built on the Gaussian process turned out to perform better than the other models, they discovered. Saksham et al, (2019) compared based and mean absolute error approaches, as well as the algorithms for machine learning that compute harvests. Rainfall, temperature and production were all taken compiled into a final dataset from the official website of the Indian government. They looked at four algorithms: Classifier XGBoost, Logistic Regression, Classifier Random Forest and Classifier KNN and calculated how accurate each was. They discovered that Random Forest was the most reliable method.

Random Forest Ensemble Method was used to improve the efficiency of the accuracy of crop yield from 92.66% of decision tree to random forest accuracy of 97.57 % which outperforms the Decision Tree Model the outcome of their model clearly shows that ensemble techniques outperform individual approaches in terms of enhancing efficiency and performance while maintaining high accuracy (Harshanand et al., 2019).In the model that was built by Sonal & Sandhya (2020), in utilizing AI algorithms to help farmers solve their crop yield challenges, deep learning (RNN, LSTM) and Machine learning (SVM) approaches were used to build the model which accuracy was 97 %. Dhivya & Durairaj, (2020) utilized deep reinforcement learning IDANN and BDN model to predict data with 93.7 % accuracy and precision above the other methods tested, according to the report. They also observed that their model has a low computational cost when compared to different deep learning techniques such as BAN, BDN, RAE, IDANN and Deep LSTN. Using artificial intelligence, one can estimate crop yield depends on the season, temperature and location were explored by Pallavi et al., (2021) suggested system includes a forecasting module which depends on the Random Forest categorization of data mining method, which is utilized to anticipate key crop yields based on historical data. Random Forest emerges as their best classifier of 98%. compared to other algorithms. Pudumalar et al., (2017) devised a crop recommendation system which can help farmers choose the greatest and most desirable crops to grow. They ended up utilizing various algorithms, such as Gaussian SVM and k-NN, after multiple tests, and developed a mechanism for conclusions meant to anticipate a result with roughly 88% accuracy. Dhivya and Durairaj (2020) combined understanding of deep learning and reinforcement learning they use deep reinforcement learning to create a comprehensive crop yield forecast system that maps raw data to crop forecast values. To anticipate crop yield, their suggested research builds a Recurrent Neural Network deep learning algorithm, which is a atop the Q-Learning reinforcement learning method. According to them, the data parameters feed the RNN Network's progressively layered layers. based on the properties of the input, Crop production forecasting is enabled by the Q-learning network. A linear layer converts the product values of recurrent neural networks into Q-values. The agent for reinforcement learning uses a boundary and a mixture of parametric characteristics to help forecast crop productivity. The suggested model's measuring performance indicators for verified data based on MAE are 0.16 for Deep learning, 0.17 for artificial neural networks, 0.52 for random forest, 0.33 for gradient boost and 0.11 for deep reinforcement learning. Their proposed model yields 93.7% accuracy. Oguntunde et al., (2018) uses support vector machine (SVM) analysis, multiple linear regressions and principal component analysis to quantify the relationships between climatic factors and rice yield. The climatic and yield data utilized covered a 36-year span from 1980 to 2015. They found out that sun radiation, pan evaporation and wind speed all decreased considerably, similar to the reported fall in rice production ($P < 0.001$). Eight main components had eigenvalues greater than one and explained 83.1% of variation in predictor variables of predictor. The SVM regression function, which used the first principal component scores, described roughly 75% of the variation in data yield of rice, while linear regression explained around 64%. Between yearly radiation sun levels and yield, SVM regression explained 67 percent of the variation. A random forest method was used to estimate sugarcane yield by (Everingham et al., 2016). They looked on the usefulness of predictor features obtained out of plant models as well as the precision of random forests in explaining yearly variance in sugarcane yields. Climate patterns prediction indicators, the highest and lowest temperatures, measured rainfall and radiation were fed into a classifier random forest, and the yearly variance in district sugarcane production was described by a random forest regression model. The model yield accuracy of 95.45%. The C4.5 algorithms were utilized by Veenadhari et al., (2014) to determine utmost influential climatic parameter on agricultural yields of chosen plants (Soybean, Maize, Paddy and Wheat) in Madhya Pradesh's selected districts. The program shows how different climate elements affect crop output in relation to each other. The algorithm yield performance Accuracy of 87% for soybean, Paddy is 85%, Maize is 76% and Wheat is 80%. In the work by Hemageetha (2016) for crop production prediction, soil factors such as Nitrogen, pH and moisture were primarily studied. The dirt was classified using the Naive Bayes method, which yielded 77% accuracy. Viviliya and Vaidhehi (2019) utilized hybrid model that takes into account geo - climatic data and suggests plants to be cultivated in southern India using the J48, Nave Bayes and association rules. The accuracy and precision gotten for Naïve bayes is 69.9% and 0.801 and that of J48 Decision Tree classifier is 95.93% and 0.883 respectively. An integrated model by Park et al., (2018) was developed for predicting rice yields in relation to climate change using Artificial Neural Networks. Crop quality was allocated to changes in yield and climatic characteristics in this model, and the crop condition was forecasted using the normalized variance vegetation figure from MODIS. The suggested model's performance is 2.91% error and correlation coefficient of 0.76.

III. CROP YIELD PREDICTION HIGH LEVEL MODEL

Figure 1 below shows the overall layout of the crop yield forecast system and its constituent parts.

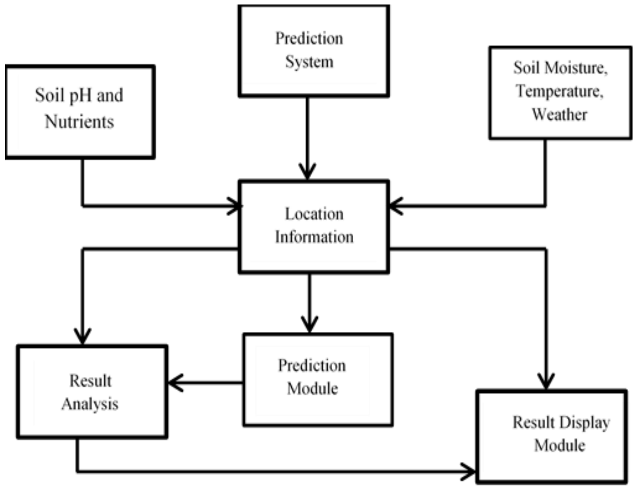

Fig 1: High Level Design of the System for Predicting Crop Yield

- Location or Plantation Information Unit: This unit manages the location or projected plantation information, which consists of meteorological information such as relative humidity, temperature, and moisture as well as soil information such as soil pH and soil nutrients.
- Module for Predicting Crop Yield: It takes the location data from the location information module and analyzes it using the constructed model to produce a prediction result that would be provided to the result analysis module. This is the core module of the system.
- Module for Results Analysis: This module would provide an understandable interpretation of the prediction's result from the prediction module. Additionally, the geographical specifics would be examined, and comments would be made to indicate the level of each aspect. The result display module would receive all of these interpreted details.
- Display Module for Results: The result display module receives the results from the prediction module along with the information from the analysis module, and organizes it to produce output on the screen. The results are displayed as bar graphs with % accuracy.

IV. METHODOLOGY

The methodology for our model follows the following steps which are the common techniques used in data mining projects.

A. Agriculture Understanding:

A bumper harvest is dependent on certain agricultural conditions that must be strictly adhered to. We understand that not every farm is suitable for all crops. An individual crop can only yield maximally in a plantation that contains the appropriate nutrients and has weather conditions suitable for its proper yield. Hence, we collected data from the Agriculture Development Project (ADP) office in Lokoja, Nigeria, and we used the information for the training of the crop yield prediction model.

B. Data Understanding:

In this step, a data understanding of the data collection was carried out through exploratory data analysis to report what the dataset entails by tabulating all the necessary parameters (Nitrogen, Phosphorous, Potassium, temperature, humidity, soil ph, rainfall and also visualize the behaviors within the dataset. Here we made use of plots and diagrams to see the relationship between the various features in the dataset. We carried out correlation heap map to know the correlation between the input parameters such as n, p, k, temperature, humidity, ph, and rainfall

C. Data Preparation:

We checked for missing value(s) and filled them, and then we moved to drop features that might reduce the accuracy of our model, keeping in mind the domain knowledge of the kind of system we are working on. Using Pearson Correlation, we did a plot for the correlation between the features in our dataset to view the distinctness and usability of the model in making the prediction. Furthermore, we normalize the available information by dropping the redundant data or the data with no importance to the model building. We also then divided the dataset into 80% for the training set and 20% for the testing set. We used the training set for the building of the model and the testing set for the validation of the model.

D. Modeling:

To train the model of the data, we used the Keras classifier (using the TensorFlow backend), the Random Forest classifier, the Decision Tree classifier, and the Gradient Boosting Classifier machine learning algorithms from the "model-selection" library of the "SKlearn" package installed into Python. The experimental results are shown in Appendix A.

E. Evaluation:

We used classification accuracy to determine the accuracy, precision, recall, F1-score, and support for the four (4) classifier algorithms we used for building the model. We visualized the result by plotting a boxplot figure of all the models according to their accuracy score using the Seaborn and Matplotlib libraries. By using the above machine learning classifiers, experimental results show that the gradient boost algorithm gives out greater accuracy in predicting the crops as depicted in the table and the plots, hence, the gradient boost classifier was used to build a crop yield prediction model.

F. Deployment:

We applied agile methodology in the deployment stage. After training the crop prediction model, we created a web app using Flask, and upon checking out the web app via a local server, the code was committed to GitHub that will be linked to Azure websites for model deployment. Individual farmers can then input their farm site parameters, and a prediction will be made on the best crop that can produce well. The user interface of the crop recommender application is shown in Figure 3.6 below. It is simple and user-friendly. When all parameters for soil and weather are correctly entered, it will predict the right crop to be planted, which will yield a bumper harvest.

V. RESULTS

The development and flow process of the Crop Yield Prediction Model consists of the following steps:

A. Step 1: Data Collection:

We collected the data compiled by Kogi State Agricultural Development Programme and we use this information for the training of the crop prediction Model.

Table 1: Data set collected

N	P	K	Temperature	humidity	Ph	Rainfall	Crop
90	42	43	20.87974	82.00274	6.502985	202.9355	Rice
85	58	41	21.77046	80.31964	7.038096	226.6555	Rice
60	55	44	23.00446	82.32076	7.840207	263.9642	Rice
74	35	40	26.4911	80.15836	6.980401	242.864	Rice
78	42	42	20.13017	81.60487	7.628473	262.7173	Rice
96	54	22	25.70197	61.3345	6.960358	83.20711	Maize
99	39	18	19.20129	68.30579	6.112751	87.85092	Maize
62	48	20	21.70181	60.47471	6.708447	95.71388	Maize
6	18	37	19.6569	89.93701	5.93765	108.0459	Cashew
8	26	36	18.7836	87.40248	6.804781	102.5185	Cashew
37	18	39	24.14696	94.51107	6.424671	110.2317	Cashew

B. Step 2: Data Cleansing and Transformation

The data we collected from the Kogi State agricultural development programme has some impurities. A cleaning process was carried out to ensure the correctness of the data and which will make it usable for the model implementation. Here also, we drop the target variable which is the crop type. The cleaned and transformed dataset is shown below:

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

Fig 2: Transformed dataset

C. Step 3: Data Exploration and Preparation

In this step, a data understanding was carried out through the exploratory data analysis to report what the dataset entails by tabulating all the necessary parameters and also visualize the behaviors within the dataset. Here we made use of plots and diagrams to see the relationship between the various features in the dataset. We also checked the number of times each crop in the 'Label' column is present. It is import that all the crops are present equally to prevent the model from making biased predictions, thereby favoring one class.

	Nitrogen	Phosphorus	Potassium	Temperature	Humidity	pH	Rainfall
count	2307.000000	2307.000000	2307.000000	2307.000000	2307.000000	2307.000000	2307.000000
mean	53.137841	52.948418	52.624187	25.554942	69.095630	6.477948	102.588546
std	39.072476	32.521784	54.920992	4.997793	24.427662	1.830180	54.045574
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.211267
25%	22.000000	28.000000	21.000000	22.747679	56.319725	5.935545	65.533776
50%	38.000000	51.000000	34.000000	25.530827	79.787252	6.405054	92.372389
75%	87.000000	68.000000	51.000000	28.436100	89.388297	6.901376	121.561271
max	179.000000	145.000000	250.000000	43.675493	99.981876	86.000000	298.560117

Fig 3: Dataset description

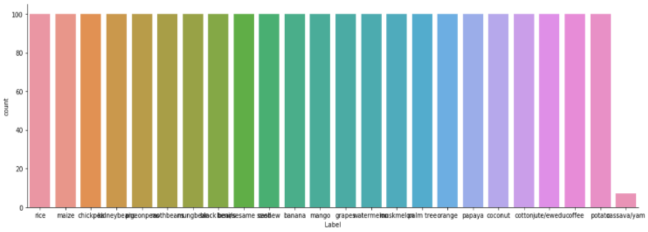

Fig 4: Bar graph to count the Target Variable

We need to drop all records with label 'cassava/yam' because it has the least number of occurrence and may serve as outliers. Since there was no missing value, next we move to dropping features that might reduce the accuracy of our model but consideration was made based on domain knowledge of the kind of system we are working on- crop prediction system. Another way to eliminate features is by checking for the correlation between these features. Using Pearson Correlation, we did a plot for the correlation between the features which showed us as a heatmap.

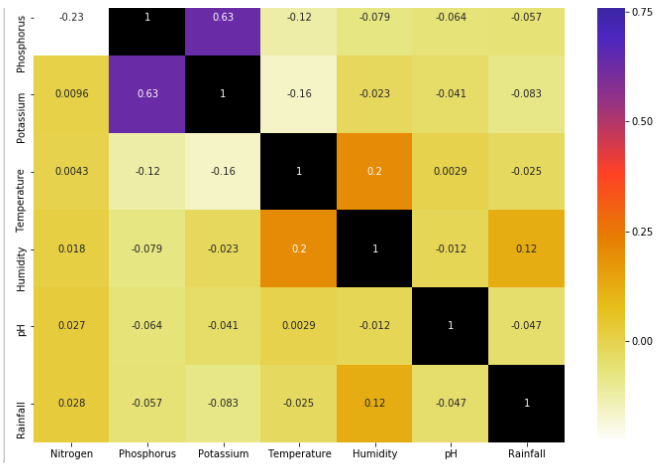

Fig 5: correlation matrix of dataset

D. Step 4: Model Training or Implementation

We trained the model of the data using four algorithms- Random Forest Classifier (RFC), Decision Tree Classifier (DTC), Gradient Boost Classifier (GBC), and Keras Classifier. from the "modelselection" library of the

ISSN No:-2456-2165

"SKlearn" package installed into the Python. We used classification accuracy to determine the accuracy, precision, recall, F1-score, and support for the four (4) classifier algorithms we used for building the model. We visualized the result by plotting a boxplot figure of all the models according to their accuracy score using the Seaborn and Matplotlib libraries. Table 4.1 reveals the comparison of accuracy among the machine learning algorithms for our dataset, the table data, shows that the gradient boost algorithm shows good prediction results for the soil, weather, and crop mapping.

Table 2: Comparison of Machine Learning Algorithms based on Accuracy, Precision and F1-Score

Model	Accuracy (%)	Precision (%)	F1-Score (%)
RFC	98.7	99.0	99.0
DTC	98.5	99.0	98.0
GBC	98.9	99.0	99.0
KERAS	94.8	-	-

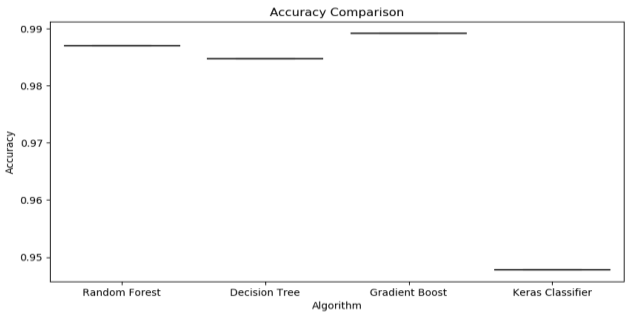

Fig 6: Comparison of Machine Learning Algorithms based on Accuracy

By using the above machine learning classifiers, experimental results show that the gradient boost algorithm gives out greater accuracy in predicting the crops as depicted in the table and the plots, hence, the gradient boost classifier was used to build a crop yield prediction model.

E. Step 5: Deployment

After training the crop prediction model, we created a web app using Flask, and upon checking out the web app via a local server, the code was committed to GitHub that will be linked to Azure websites for model deployment. Individual farmers can then input their farm site parameters, and a prediction will be made on the best crop that can produce well. The user interface of the crop recommender application is shown in Figure 4.6 below. It is simple and user-friendly. When all parameters for soil and weather are correctly entered, the outcome of the processes in the system presents the user with the anticipated information on the right crop to be planted which will yield a bumper harvest.

Fig 7: Crop prediction user interface

VI. DISCUSSION

From our results, data that involve integration of soil nutrients-nitrogen, phosphorous, potassium, soil pH and location weather are good for crop yield prediction.

The model deployed for use with the prediction system was evaluated based on certain metrics to know how well it performs towards achieving the prediction goal. The metrics used for the performance evaluation are accuracy, precision, and F1-Score. Below is the performance evaluation for the four algorithms used. Random Forest Classifier (RFC), Decision Tree Classifier (DTC), Gradient Boost Classifier (GBC), and Keras Classifier.

Table 3: Model Performance Evaluation

Model	Accuracy (%)	Precision (%)	F1-Score (%)
RFC	98.7	99.0	99.0
DTC	98.5	99.0	98.0
GBC	98.9	99.0	99.0
KERAS	94.8	-	-

It is also deduced from the results that Gradient Boosting Classifier gave the accuracy of 98.9%, Random Forest Classifier gave 98.7%, Decision Tree Classifier gave 98.5% and Kerass Classifier gave 94.8%. It implies that, they are all good algorithms to develop the crop yield prediction model. The Kerass Classifier have less accuracy and thus, it is not a best algorithm for developing the crop yield prediction model.

We emphasized on Gradient Boost Classifier, as it attempts to separate the target classes with the widest possible margin. These results show the capacity of Gradient Boost Classifier in crop type prediction, and that, to modify the model accuracy, is a characteristic of applying the right kernel-trick.

Gradient boost classifier; being the best of all algorithms with the accuracy of 98.9% was used to build our crop prediction model. The best accuracy obtained so far was 97% our own improved on previous work done by almost 2%.

Crop yield prediction would become better and more accurate using the Integrating Soil Nutrients and Location Weather for Crop Yield Prediction System developed in this project. Using features based on soil nutrients, weather, or pH to get a prediction is less accurate; this system combined soil nutrients, soil pH, and location weather for crop yield prediction for twenty-three different crops. So, our model is not limited to only one crop. The approach is an ongoing process in which assessment metrics can be improved, mining can be refined, and fresh data can be merged and translated to provide new and more relevant findings. Finding patterns or information in an existing database is part of the process. The data for this project was obtained from a database, making the approach appropriate for this project and considering the many procedures involved, making the analysis and construction of the suggested model simple. Our user interface was also simple, user friendly and easy to operate. Using android phone or computer system connected to internet or any application program interface (API), farmers can upload their proposed plantation parameters and get appropriate crop for their farmland.

VII. CONCLUSSION

The recommended model was developed using machine learning Gradient Boost Classifier (GBC) techniques to assist farmers in reducing farm losses caused by a lack of knowledge of cultivation in various soil and weather conditions. The model predicts the best crops to grow on land while spending the least amount of money. After evaluation of the prediction metrics it is concluded that there is an enhancement in the accuracy of this research work when compared to the existing work that used other techniques for crop yield prediction. The accuracy is determined to be 98.9%. It has a promising future and can be integrated with a versatile and multi-skilled application. The farmers need to be educated and consequently, will obtain clear information regarding maximum crop production via their mobiles. With all this, even when the farmer is at home, the task can be handled at that given point in time, without experiencing any loss ahead. The advancement in the sector of agribusiness will be incredibly beneficial, assisting farmers in the yield of crops.

A reliable and resource-saving crop yield prediction system was developed in the course of this research project. The system comprises two major parts: the user interface designed with python flax framework and the machine learning model (along with some python scripts) that serves as the backend of the system. The interface enhances easy and smooth interaction between the user and the model; a machine-learning model with an accuracy of 98.9% can be reliable for crop yield prediction.

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