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Optimizing Agricultural Outcomes: Machine Learning in Crop Yield Prediction

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Abstract

Digital agriculture is becoming more and more in demand as a result of the quick advancement of information technology. Crop yield has always garnered a lot of interest as a significant problem in agricultural production. At the moment, machine learning and artificial intelligence in general are the most popular methods for predicting agricultural productivity. Consequently, one of the main problems in digital agriculture is creating a machine learning technique that can reliably forecast crop yield. Crop yield prediction has a strong time correlation, in contrast to conventional regression prediction problems. For instance, there are significant temporal correlations in the weather data for every county. Furthermore, crop yield is somewhat impacted by geographic data from various places. For instance, a county is likely to have large yields if its neighbouring countries have a strong harvest. We used models like random forest, decision tree classifier, support vector machine, KNN, and logic regression in this study. With an accuracy score of 99.77%, random forest produced the greatest results out of all of them.

Keywords: Quantum Machine Learning (QML), Quantum Algorithms, Variational Quantum Circuits (VQCs)

INTRODUCTION

Given that agricultural yields are unpredictable and conventional farming is susceptible to risky climate and natural catastrophes, major natural tragedies have the potential to reduce crop yields and result in substantial losses. However, it will significantly advance the development of modern agriculture and help prevent substantial losses if different data of climate and soil can be combined to forecast upcoming crop yields and provide premature cautions for possible calamities. The idea of digital agriculture, which seeks to use computers to forecast future agricultural production, has been put forth in response to this demand. A crop growth model (Fritz, S. et al. 2019; Hameed et al.,2019; Gavasso-Rita. Et al. 2024; Jones J. W et al. 2017) can be used to forecast crop yield by simulating plant growth and development using underlying physiological mechanisms. A crop growth model, however, has some limitation (Shahhosseini, et al. 2021; Zhang et al. 2023). For instance, some approaches' descriptions of particular procedures are either unclear or unduly simplified, which reduces crop prediction accuracy. Furthermore, calibrating the crop growth model's parameters requires a substantial investment and extremely specialized topic expertise. Machine learning (Murphy et al. 2012), on the other hand, is data-driven and superior than the crop growth model in handling intricate nonlinear interactions. Crop production prediction has long made use of a variety of machine learning techniques (Shingade et al. 2024), including support vector machines (Khaki, et al, 2019), artificial neural networks (Sarr et al. 2023), and decision trees (Ransom, C. J. et al 2019; Younis et al.,2020). Despite its notable advancements in agricultural production prediction, machine learning has many drawbacks. For instance, machine learning techniques limit the model's scalability and generalizability by requiring manual extraction of features to enhance the predictive capacity of the model. Furthermore, current machine learning techniques might not work good on big datasets, such as the whole nation, because they are typically built on tiny, self-collected regional datasets. Deep learning based on Neural network (Fan et al 2022; Khaki et al. 2020; Shen et 2022), a machine learning extension, has grown in popularity in the crop production prediction field in current years due to the rapid development of deep learning. The primary benefit of deep learning over conventional shallow machine learning models is its strong feature extraction capabilities, which eliminate the requirement for expert human feature extraction. Consequently, in agricultural crop prediction applications, deep learning models typically exhibit superior flexibility, generalization, and proficiencies to learn features.

Current techniques for predicting agricultural yields based on deep learning usually concentrate on simulating temporal correlations within a dataset. However, they consider each country as an independent and identically distributed (i.i.d.) sample in their models, ignoring the crucial role that geographic links play in crop production prediction. In actuality, crop prediction also heavily relies on the geographic relationships between countries. The yields in surrounding counties, for instance, are typically not independent; that is, if a country's adjacent countries have a strong crop, this country is expected to have high harvests similarly. A framework using deep learning to predict agricultural yields was recently published (Hamilton, W. et al 2017), and it uses a graph neural network (GNN) model (Velickovic et al 2017) to represent the geographic links between counties. However, GNN makes the assumption that all nearby nodes have the same structure, which could result in the loss of crucial spatial information and make it impossible to take into consideration how various bordering counties affect yield predictions. Prediction accuracy may be compromised as a result of this lack of difference, which could lead to less-than-ideal modeling of geographic linkages. For precise crop production prediction, it is crucial to create added efficient models that better utilize both temporal and geographical information.

LITERATURE REVIEW

Current machine learning methods for crop prediction can be broadly divided into two categories: deep learning-based methods and classic machine learning-based methods. Conventional Machine Learning-Based To forecast agricultural yields, a number of studies have employed conventional machine learning-based techniques, such as random forest, K-nearest neighbor (KNN), artificial neural networks, and gradient boosting.

Random forest

Using the characteristics of soil and climate from a local database in the Midwest of the United States, (Curtis J. Ransom et al 2019) assessed many models of machine learning and showed that the random forest approach performed better than the ridge regression and stepwise regression models. Built on meteorological history of yield data, (Kuradusenge et al. 2023) suggested ML models, such as support vector regressors and random forest, to forecast crop yields (i.e., corn and Irish potatoes) in the Rwanda's Musanze region. Using the Extra Trees Regressor, (Nikhil U. V et al. 2024) developed ML models to forecast the production of a variety of crops, including rabi, sugarcane, rice, sorghum, and cotton. Of the models tested, this one performed the best.

KNN.

Using K-means and a modified KNN, (Suresh et al. 2018]) suggested a prediction approach for Tamil Nadu, India's main crops. (Karn R. K et al. 2023) used a dataset of 2200 rows and 22 columns of data from Kaggle to study a system to recommend crops using the KNN algorithm. Using a dataset collected from Kaggle for various crops, (Kumar et al. 2203) have suggested KNN algorithm for suggestion of crops.

Neural network

Sarr et al. (2023) predicted agricultural crops (sorghum, peanut, millet and maize) in 24 Senegalese departments using a variety of machine learning techniques, such as neural networks, support vector machines, and random forests. Soil conditions for crop production prediction are not included in the dataset. (Das et al. 2023) suggested a hybrid strategy to forecast agricultural yields by fusing support vector regression (SVR) or an artificial neural network with the feature selection technique, MARS. They used a limited dataset of lentils for their experiments. Neural network techniques fared better than previous machine learning models that (Sadenova et al. 2023) developed for forecasting crop yield in eastern Kazakhstan. The remote sensing data used in this dataset was sourced freely.

Gradient boosting

Shahhosseini et al. (2019) used a factorial simulation experiment to simulate dataset for assessing the capability of several ML methods for predicting nitrate loss and maize yield. They concluded that the most accurate ML model is XGBoost. Gradient boosting regression was used by (P. Mishra et al. 2020) to forecast crop production for French areas. Gradient boosting regression was suggested by (Pradeep et al. 2023) as a way to forecast crop yield for Indian districts. On a Kaggle dataset, (Yasaswy et al.,2022) demonstrated superior crop prediction performance using gradient boosting over random forest.

Deep Learning-Based

Models based on Neural network, such as LSTM and CNN, have gain in popularity in the field of crops production prediction in recent years due to the quick growth of deep learning. The aforementioned conventional shallow machine learning methods are usually limited to short datasets and necessitate manual feature extraction. Deep learning models, on the other hand, work better on bigger datasets and have built-in feature extraction capabilities.

CNN

In order to excerpt spatial association landscapes for agricultural production forecast, some publications have proposed frameworks of deep learning, for example CNN. A deep neural network model was created by (Khaki et al. 2020) to forecast corn yield at 2247 US sites. Using optimum input variables from meteorological datasets and satellite products (Kim et al. 2019) created a model of deep neural network for predicting crop output in the midwestern United States between 2006 and 2015. Using a dataset gathered at the district Agra in the (UP) Uttar Pradesh province of India, (Kumar et al. 2023) suggested a mixture autoencoder deep capsule with softmax regression (Hybrid DCAS) model. For the crop, (Subramaniam et al. 2024) suggested dimensionality reduction (DR) and weight-tuned deep convolutional neural networks (WTDCNN).

LSTM

Deep learning frameworks, including LSTM, have been proposed in certain research to excerpt temporal connection characteristics for agricultural yield forecast. In order to forecast wheat crop in the Xinxiang, Province Henan in China, (Shen et al. 2022) suggested a framework that combines a long short-term memory NN with RF (LSTM-RF). Thermal and multispectral sensors were used to collect the remote sensing datasets. In order to lower the testing and training loss in crop forecasting, Bhimavarapu et al. (2023) suggested a novel and improved optimization function (IOF) to train the LSTM model. The dataset was gathered from Indian districts. Using a remote sensing dataset from China's Henan Province, (Wang et al. 2022) suggested an LSTM model for predicting wheat crop. Using satellite meteorological data from Hengshui, Hebei Province of China, (Di et al., 2022) developed a model based on Bayesian optimization long short-term memory model (BO-LSTM) for building a multiple source data fusion-driven harvest growth algorithm to extract features for yield forecasting of winter wheat. DeepCropNet (DCN), a deep learning framework based on LSTMs, was proposed by (Lin et al. 2020). It can efficiently forecast corn yields at the county level in the US by hierarchically capturing characteristics. Using data from Pakistan's Federal Bureau of Statistics, (Haider et al. 2019]0 suggested an LSTM neural network model for forecasting wheat production in Pakistan.

CNN-LSTM

In order to extract spatiotemporal connection characteristics for agricultural production prediction, some additional publications have developed hybrid deep learning frameworks, such as CNN-LSTM. A hybrid CNN-LSTM model was suggested by (Khaki et al. 2020) and was successful in properly predicting crop yields throughout the US Corn Belt. The suggested approach fared noticeably better than other well-liked techniques including CNN, LASSO, and random forest. To further increase accuracy, (You et al. 2017; Zahra et al.,2019; Hameed et al.,2018) included a Gaussian process component to their CNN-LSTM model, which they used to capture spatiotemporal structures in the data. In order to help the model identify useful characteristics in sparse training data, they also presented a novel dimensionality reduction technique. CNN-BI-LSTM-CYP is a deep learning method for sugarcane yield prediction that was proposed by (Saini et al. 2023). The primary sugarcane-producing states in India provided the dataset. (Boppudi et al. 2024; Shehzadi et al.,2021) suggested a hybrid LSTM-DBN model for crop prediction in India as well as an enhanced feature ranking fusion procedure for feature selection.

Proposed work

Aim of this article is to extract the deep insights of the dataset and find the best predictive model so as to suggest most suitable crops to grow based on the available climatic conditions and soil conditions.

In the data Analysis We used various Python Libraries such as pandas, Numpy, Seaborn & Matplotlib.

Total number of rows are = 2200

Total number of columns are = 8

Total number of unique crops in our dataset are 22

Now we draw a chart that describe the mean of all crop requirements based on each crop.

Crops	N	P	K	temperature	humidity	ph	rainfall
apple	20.800000	134.220000	199.890000	22.630942	92.333383	5.929663	112.654779
banana	100.230000	82.010000	50.050000	27.376798	80.358123	5.983893	104.626980
blackgram	40.020000	67.470000	19.240000	29.973340	65.118426	7.133952	67.884151
chickpea	40.090000	67.790000	79.920000	18.872847	16.860439	7.336957	80.058977
coconut	21.980000	16.930000	30.590000	27.409892	94.844272	5.976562	175.686646
coffee	101.200000	28.740000	29.940000	25.540477	58.869846	6.790308	158.066295
cotton	117.770000	46.240000	19.560000	23.988958	79.843474	6.912675	80.398043
grapes	23.180000	132.530000	200.110000	23.849575	81.875228	6.025937	69.611829
jute	78.400000	46.860000	39.990000	24.958376	79.639864	6.732778	174.792798
kidneybeans	20.750000	67.540000	20.050000	20.115085	21.605357	5.749411	105.919778
lentil	18.770000	68.360000	19.410000	24.509052	64.804785	6.927932	45.680454
maize	77.760000	48.440000	19.790000	22.389204	65.092249	6.245190	84.766988
mango	20.070000	27.180000	29.920000	31.208770	50.156573	5.766373	94.704515
mothbeans	21.440000	48.010000	20.230000	28.194920	53.160418	6.831174	51.198487
mungbean	20.990000	47.280000	19.870000	28.525775	85.499975	6.723957	48.403601
muskmelon	100.320000	17.720000	50.080000	28.663066	92.342802	6.358805	24.689952
orange	19.580000	16.550000	10.010000	22.765725	92.170209	7.016957	110.474969
papaya	49.880000	59.050000	50.040000	33.723859	92.403388	6.741442	142.627839
pigeonpeas	20.730000	67.730000	20.290000	27.741762	48.061633	5.794175	149.457564
pomegranate	18.870000	18.750000	40.210000	21.837842	90.125504	6.429172	107.528442
rice	79.890000	47.580000	39.870000	23.689332	82.272822	6.425471	236.181114
watermelon	99.420000	17.000000	50.220000	25.591767	85.160375	6.495778	50.786219

Figure 1.

From above chart we found that

1) Cotton required maximum Nitrogen Followed by Coffee and Banana \ 2) Apple required maximum Phosphorous Followed by Grapes \ 3) Grapes required maximum Potassium Followed by Apple \ 4) Papaya required maximum Temperature (>30 C) Followed by Mango (>30 C)

Now we plot N-P-K values of each crop.

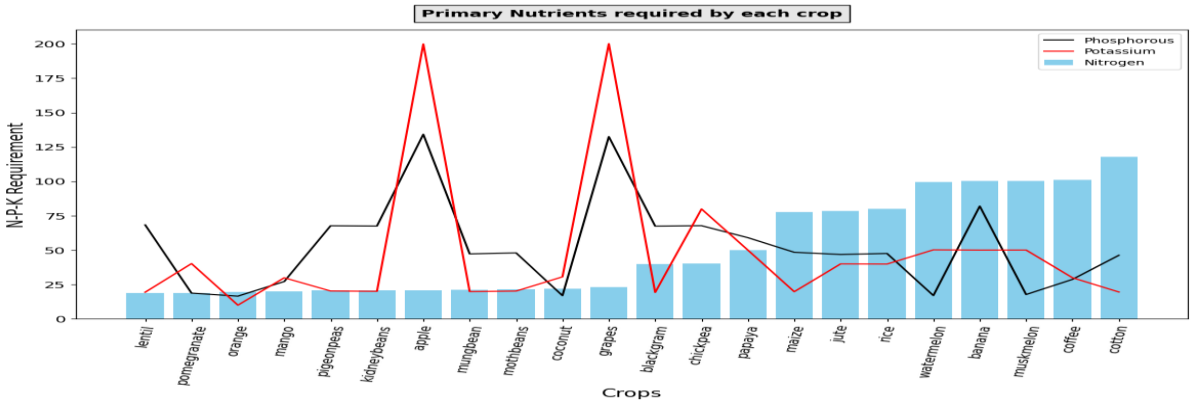

Figure 2.

1) N-P-K requirement of Orange,Mango and Coconut are very low.\ 2) P-K requirement of apple and grapes are very high but they require less Nitrogen.\ 3) Cotton require High N but less P-K.

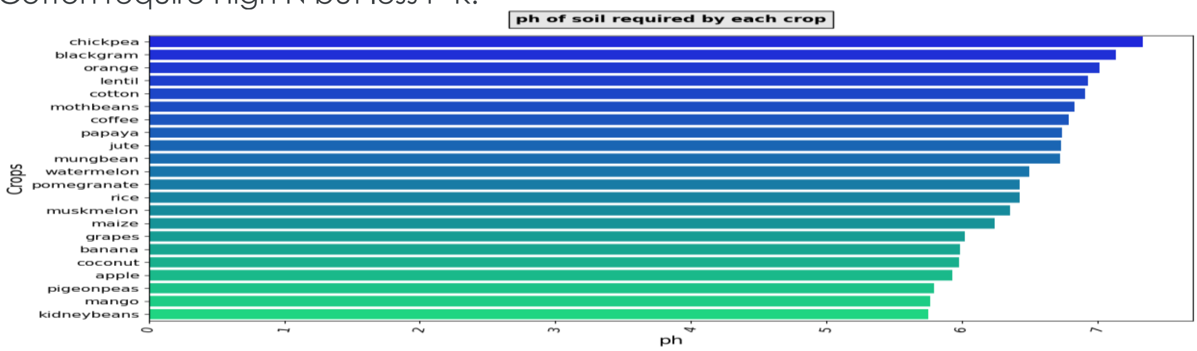

Figure 3.

From this plot we found that all crops require ph more than 5.5.\ 2) Chickpea require high ph followed by blackgram.\ 3) mango and kidneybeans require minimum ph (approx 5.7) to grow.

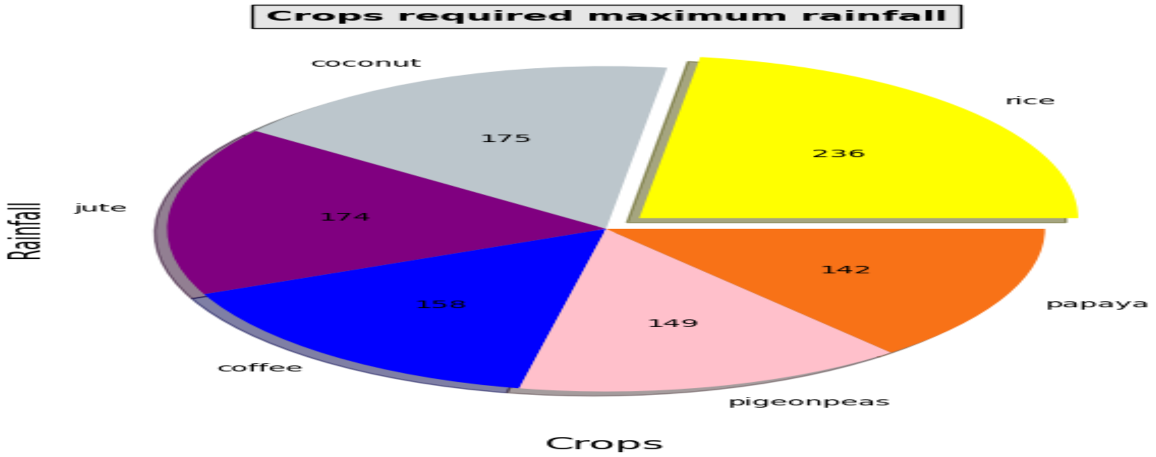

Figure 4.

From above plot it was observed that: Rice require maximum rainfall(>220 mm) followed by Coconut(175 mm) and Jute(174 mm).

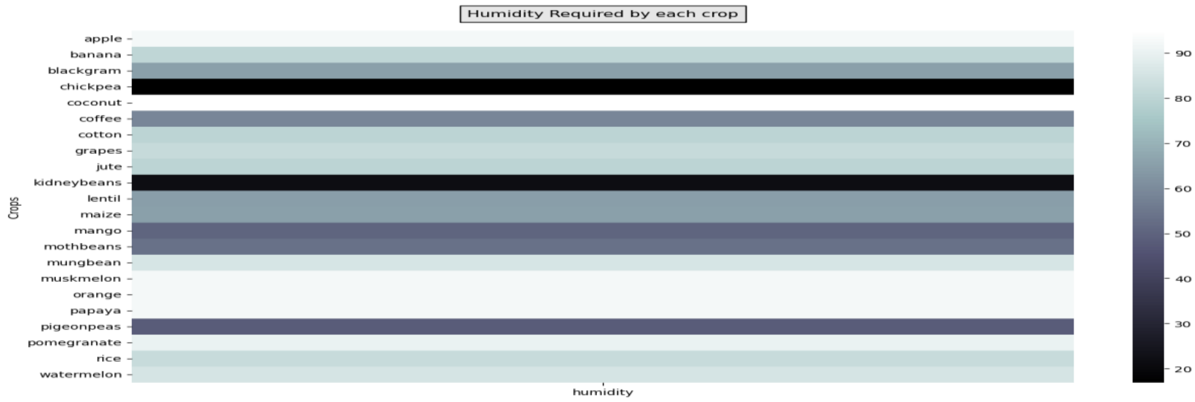

Figure 5.

Observation from above plot: 1) chickpea and kidneybeans requires very less humidity to grow.\ 2) Coconut require very high humidity to grow

Now we check the temperature range of each crop in which crop can grow.

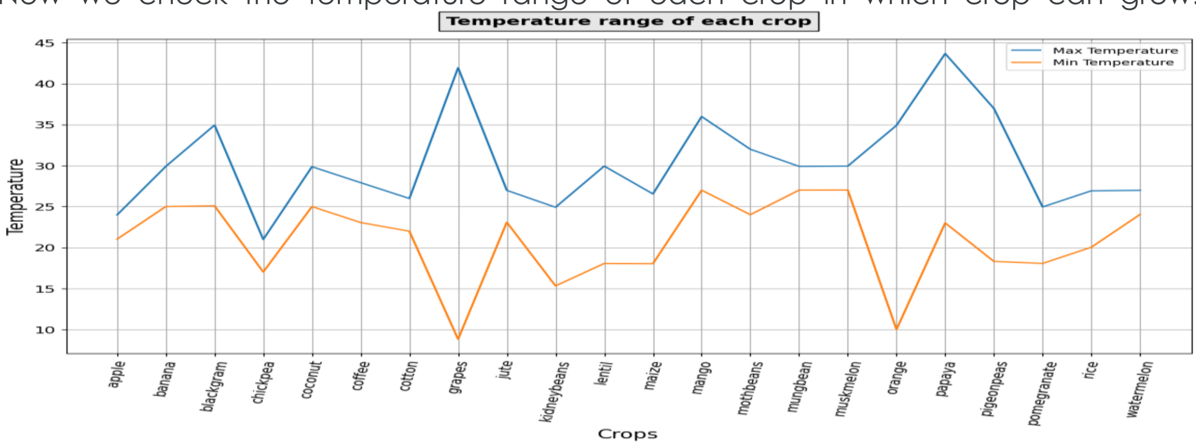

Figure 6.

From above study we found that grapes, orange, papaya has a large range of temperature means they can grow in any season if other variables are arranged accordingly.

Now we categorise crops based on Summer, Winter and Rainy season.

		Crops
Summer Crops	0	blackgram
	1	grapes
	2	mango
	3	mothbeans
	4	orange
	5	papaya
	6	pigeonpeas
Winter Crops	0	grapes
	1	lentil
	2	maize
	3	orange
	4	pigeonpeas
	5	pomegranate
Rainy Crops	0	coconut
	1	papaya
	2	rice

Figure 7.

From above table, we can check which season is suitable for cultivating any crop. Now we do some advance analysis in above table: As we can see some crops are appearing in more than one season such as grapes, orange, papaya etc, so now we check which season is more favorable for that particular crop based on data.

	Crops	Summer_Count	Winter_Count	Rainy_Count
0	blackgram	48.000000	0.000000	0.000000
1	grapes	27.000000	41.000000	0.000000
2	mango	36.000000	0.000000	0.000000
3	mothbeans	14.000000	0.000000	0.000000
4	orange	23.000000	36.000000	0.000000
5	papaya	68.000000	0.000000	26.000000
6	pigeonpeas	14.000000	16.000000	0.000000
7	lentil	0.000000	11.000000	0.000000
8	maize	0.000000	27.000000	0.000000
9	pomegranate	0.000000	30.000000	0.000000
10	coconut	0.000000	0.000000	26.000000
11	rice	0.000000	0.000000	80.000000

Figure 8.

From above analysis it was found that grapes can grow in summer and winter season but it is more favorable to grow it in winter season.\ 2) Orange can grow in summer and winter season but it is more favorable to grow it in winter season.\ 3) grapes can grow in summer and winter season but it is more favorable to grow it in winter season.

Building models and compare their accuracy.

Now we break our dataset into two parts: 1) Dependent variables 2) Independent Variables

Now we break our data into train and test part in ratio 80:20.

Final step is to build different models and compare their accuracy and find the best model for our dataset.

Accuracy Score of logistic Regression: 0.9693181818181819

Accuracy Score of KNN: 0.9772727272727273

Accuracy Score of Support Vector Machine: 0.9772727272727273

Accuracy Score of decision tree classifier: 0.9931818181818182

Accuracy Score of Random Forest: 0.9977272727272727

Random forest gave us the best results

Now we test its score with training data which we used to train it.As we train our data with training dataset so prediction with same dataset should be 100%

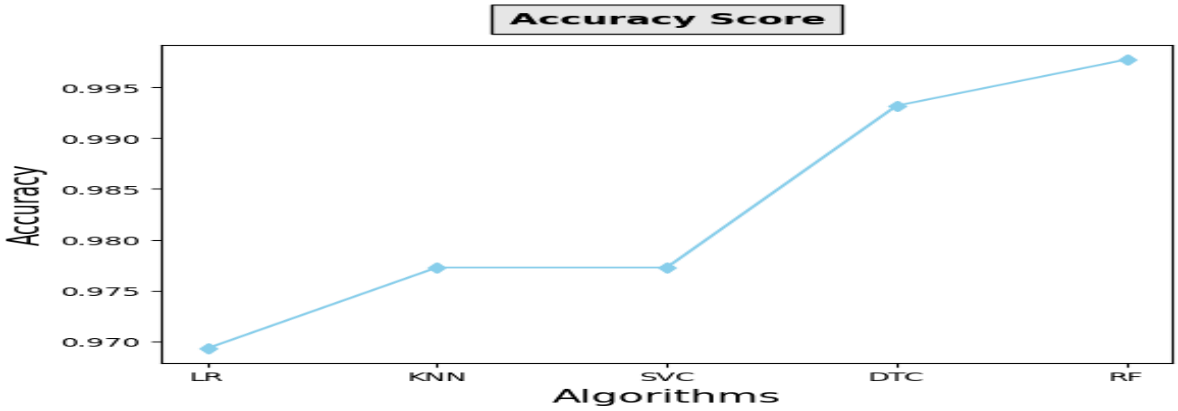

Figure 9.
Random Forest's Accuracy score 1.0.

CONCLUSION

Agriculture optimization using machine learning is a modern approach that involves t he use of artificial intelligence to enhance the efficiency of agricultural practices. Thi s technology leverages data from various sources to provide insights that can help fa rmers make better decisions on crop management, soil health, weather patterns, an d other critical aspects of farming. By optimizing agriculture, we can improve crop yi elds, reduce waste, and ultimately, ensure food security for the world's growing popu lation. Machine learning algorithms can predict crop performance, detect diseases early, and recommend the most efficient use of resources, thereby minimizing waste and maximizing productivity. Furthermore, as global food demand continues to rise w ith the increasing population, optimizing agricultural practices through technology is key to ensuring sustainable food production. This technological revolution has the po tential to boost crop yields, improve resource efficiency, and strengthen food securit y worldwide. Ultimately, the integration of machine learning into agriculture not only enhances farm productivity but also contributes to a more resilient and sustainable g lobal food system.

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Consent to Participate: Yes

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