A Machine Learning-based Inference and Analysis of Crop Production based on Climate Parameters in Bangladesh

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Abstract

As a traditionally agricultural country, Bangladesh has a major economic dependency on the crops it grows. Predicting the production of crops is a significant part of the economic program of the country. Among the many domains that can be used to perform the prediction, this report adopts the parameters of the weather to foretell the production of crops. Correlating between the yield of crops and the climate has been widely experimented upon across the globe. This study adapts and improves on the techniques and processes introduced in previous studies to derive a broader, localized and intuitive correlation between the two entities. Using standard approaches of machine learning – linear regression, support vector machine, random forest and more – this paper not only provides appropriate prediction models for all the crops considered but also infers the numeric effect of various climate factors on the unit production of the crops.

Keywords: Machine learning, Crop production, Linear regression, Support vector machine

1. Introduction

Agriculture is a significant aspect in the economy and prosperity of Bangladesh. Even in the modern era of industrialization, agriculture is responsible for 14% of the nation's Gross Domestic Product (GDP) [10]. Agriculture provides a major portion of the country's employment despite the advent progression of urbanization and industrialization. Approximately 87% of the rural population is dependent on agriculture in some way for their livelihood [10]. Agriculture also plays a vital role in the nation's policy making. 3.7% of the annual budget of the country is deployed for the growth and sustenance of agriculture [11]. These factors perfectly describe the dependency Bangladesh has on its agriculture. The opportunity to predict the production of the homegrown crops is therefore very important for the people and economy of the country.

Predicting the annual yield of crops will be directly beneficial to various demographics related to agriculture. A comparative estimation of the total production of multiple crops can help farmers and land owners decide on which crop to invest in. Businessmen can use the information for pricing and storage. Policymakers can utilize the findings by emphasizing policies and funding on the advancement of the appropriate crop. To conduct such prediction, data is needed on features which influence the production of crops along with previous production data of said crops. Collecting this data is a challenging task due to the distributed, occasionally incomplete and partially organized nature of the sources. The next challenge arrives in the processing of the data. The features need to be appropriately organized and examined to filter out unnecessary or counterproductive data. Lastly, it is necessary to prepare not only a predictive model that provides the most accurate estimation but also an intuitive model that can be interpreted by the general populace.

Similar works on this field have tackled different aspects of the problem using a variety of statistical and machine learning methods. The works have yielded results that are significant in determining the corre-

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lation between climate and crop production. Studies emphasizing on the agriculture of foreign lands pave a structure for inferring and predicting the problem. Crane-Droesch [2] implements SNN and OLS regression to correlate climate factors and corn production. Works that are undertaken for Bangladesh encounter the problem in different manners adapting to the limited data and resources available. Ahamed et al. [3] uses data collected from the years 2009-10 and 2010-11 to predict crop production of five different crops with five different weather parameters. Shakoor et al. [4] applies decision tree and KNN regression to predict 6 crops with data from the years 2004-2013. The domestic researches have limitation of data used, with a limited set of environmental predictors. Although some of the papers consider seasonal impacts of weather, few establish a human readable correlation between crop production and the different climate factors.

Crop production can be estimated using various factors that can span administrative and financial domains. This report uses weather as the core aspect for predicting crop yield. Weather has multiple parameters that include temperature, rainfall, humidity and much more. The prediction model is built on the correlation between the seasonal averages of climate parameters and the annual production of crops. Six of the most fundamental crops were included for prediction – AMON rice, AUS rice, BORO rice, jute, wheat and potato. Their annual production is documented according to the fiscal year (July to June). Data on the climate parameters are stored monthly which can be grouped based on the three major seasons of Bangladesh – summer, monsoon and winter. Therefore the correlation is established between the seasonal weather reports from January to December and the annual crop production of the fiscal year that starts from the July of that year.

This report concludes on two different findings. Firstly, it was able to generate an inference scheme using the linear regression model. The regression shows the estimated effect of crop production based on the unit change of weather parameters that are significantly influential to the crop. It is seen that the resulting model is different for each crop as they are not only affected by distinct sets of parameters but also with varying degrees. Secondly, single best models of predictions were derived for each of the crops using Root Mean Squared Error (RMSE) as the metrics of comparison. Six different machine learning methods were applied and the method with the least error was chosen as the suggested model to use.

2. Related Work

Predicting the production of crops based on the climate has been a popular research area both locally in Bangladesh and internationally. The researches apply different machine learning techniques to a variety of data to encounter the problem. This section provides a brief review on these researches and discusses the improvements this report hopes to bring.

2.1. Local Literature

Due to the national importance of agriculture, multiple researches on predicting crop production with weather parameters have been conducted in Bangladesh. Ahamed et al. [3] use data mining techniques to predict crop yield using environmental parameters like rainfall, maximum and minimum temperature, humidity and sunshine among other predictors of the years 2009-10 and 2010-11. Amon, Aus and Boro rices, potato and wheat are the crops which are predicted. K-means clustering is applied to cluster the 15 districts into 4 types of geographical clusters, and 3 data mining techniques - linear regression, KNN and artificial neural network - are used to predict crop yield. It is observed that artificial neural network is the best predictor for wheat, potato and Aus rice while linear regression is the best fit for Amon and Boro rices.

Amin et al. [5] experiment on Aus rice, Amon rice, Boro rice and wheat from 1972 to 2010. Correlation is derived between the yield of the crops and the change in climate parameters – temperature, rainfall, humidity and sunshine. Applying the HAC and FGLS methods show that Amon rice is influenced by maximum temperature and rainfall among other relationships.

Production of three kinds of rices – Aus, Amon and Boro – are predicted using a combination of neural networks and support vector machine in Hossain et al. [6]. The data of 21 regions are considered with three predictors – monthly temperature, humidity, rainfall. A significant correlation is documented between the weather parameters and rice yields.

The correlation between weather and crop production is also explored by Shakoor et al. [4]. Decision tree and KNN regression algorithms are used with monthly temperature and rainfall for the years 2004 to 2013. Aus, Amon, Boro, jute, wheat and potato of 10 districts are predicted with a very high accuracy.

This report improves on the experimentation and findings of these researches. Firstly, a bigger dataset is collected, processed and used for the models starting from 1970. Secondly, a total of 6 crops are considered – Aus, Amon and Boro rice, jute, wheat and potato. Thirdly, more environmental parameters are used which are pre-processed by dividing those into four distinct seasons to better understand the impact of the seasonal weathers. Lastly, not only are predictions made using 6 distinct models but inference is made using regression models for representing the findings for the laymen.

2.2. Foreign Literature

The study of weather patterns influencing agriculture using statistics and machine learning is an internationally popular field of research. Crane-Droesch [2] examines the impact on climate change on crop yields using corn data in the US Midwest. The correlation is generated with semi-parametric neural networks and OLS regression on 12 different climate parameters that include precipitation, air temperature, relative humidity, wind speed and more. It is observed that machine learning techniques derived a more optimistic result than statistical approaches on the impact of climate change on corn production.

Crop production in the Madhyapradesh state of India is observed by Veenadhari et al. [7]. Weather parameters – cloud coverage, rainfall and temperature – are used to predict the production of soybean, paddy, maize and wheat using decision trees. The resulting accuracy is 75% on average.

Similarly, the crops of Tamilnadu is experimented on by Priya et al. [8] with one crop – rice. Applying random forests, weather parameters like maximum temperature, rainfall and more are used to correlate with the production of rice, resulting in an accurate estimation.

Lastly, Gonzalez-Sanchez et al. [9] experiment on 10 different crops in the irrigation areas of Mexico. As predictors, 8 different parameters are used including weather parameters such as minimum, average and maximum temperature and rainfall. 5 different machine learning techniques are applied for the predictions – multiple linear regression, regression trees, artificial neural network, support vector machine and k nearest neighbour. Different models are chosen as the best techniques for the crops based on RMSE, RRSE, R and MAE.

The researches mentioned above are indicative of the significance of climate parameters on the production of crops. This study adopts different techniques used in these researches with the domestic data to experiment on the crops and weather of Bangladesh.

3. Methodology

The approach taken to build the prediction model consisted of three steps. The first step involved collecting the relevant weather data along with data on crop production. This was followed by preprocessing the data, verifying their testability and choosing the appropriate predictors for the individual crops. Finally, the predictors were used in various algorithms to create multiple data models which were later compared to decide on the best fitting model to predict crop production from weather parameters.

3.1. Data Collection

Firstly, the data of annual production of the crops were collected from Bangladesh Bureau of Statistics' report on “45 Years Agriculture Statistics of Major Crops” [12]. The dataset consists of the total crop yields of fiscal years starting from 1970-71 to 2014-15.

Next the data on different weather parameters were collected from various sources. Data for temperature and rainfall were collected from World Bank climate portal [13]. Monthly averages of both attributes were collected from the year 1970 to 2014. Four parameters – relative humidity, bright sunshine, wind speed, and cloud coverage – were collected from Bangladesh Agriculture Research Council’s online dataset [14]. The monthly averages of 35 weather stations from the year 1948 to 2013 are stored in the source. From that the national average from 1970 to 2013 were collected. Yearly statistics of flood was collected from Bangladesh Water Development Board’s Annual Flood Report 2013 [15]. Annual statistics on earthquakes, cyclones and drought were collected from Bangladesh Statistical Yearbook 2017 [16].

Climate parameters that are monthly, were grouped to derive seasonal outputs. A single year in Bangladesh consists of 3 major seasons – summer, monsoon and winter. Winter comes twice in the year. Therefore, monthly data were divided in four different groups – winter 1 (January to February), summer (March to June), monsoon (July to October), and winter 2 (November to December).

Table 1: Descriptive Statistics (Minimum, Maximum, Mean and Standard Deviation) of the Data

Type	Name	Acronym	Max	Min	Mean	Sd
Predictor	Temperature (C) for Winter 1	tw1	21.48435	18.36005	19.61433977	0.710997823
	Temperature (C) for Summer	ts	28.3245	25.5883	26.96344545	0.607864055
	Temperature (C) for Monsoon	tm	28.5507	27.1423	27.90216364	0.288738262
	Temperature (C) for Winter 2	tw2	22.7669	20.1703	21.56851136	0.613900669
	Rainfall (mm) for Winter 1	rw1	32.22115	0.134545	13.34621159	7.782990573
	Rainfall (mm) for Summer	rs	251.864133	66.5748	156.6996242	49.41039255
	Rainfall (mm) for Monsoon	rm	466.8222	272.241	358.6328536	55.08339655
	Rainfall (mm) for Winter 2	rw2	72.8354	0.8181	21.61097455	19.11814274
	Relative Humidity (%) for Winter 1	hw1	78.84848	67.86207	73.28145091	3.012414109
	Relative Humidity (%) for Summer	hs	79.11458	68.88889	74.69285159	2.265495064
	Relative Humidity (%) for Monsoon	hm	87.53939	83.26667	85.47958409	0.87765369
	Relative Humidity (%) for Winter 2	hw2	82.34848	72.33333	77.88024705	2.510073029
	Bright Sunshine (Hours) for Winter 1	bw1	10.05714	6.085294	7.769883432	0.896493519
	Bright Sunshine (Hours) for Summer	bs	8.904762	6.514141	7.641592932	0.565818489
	Bright Sunshine (Hours) for Monsoon	bm	5.86	4.216774	4.99667925	0.365099943
	Bright Sunshine (Hours) for Winter 2	bw2	9.142857	5.9	7.577373136	0.766462328
	Wind Speed (mps) for Winter 1	ww1	2.498571	0.567647	0.991252205	0.493333978
	Wind Speed (mps) for Summer	ws	3.298958	1.084314	1.864758545	0.524985452
	Wind Speed (mps) for Monsoon	wm	2.572571	1.051765	1.601016295	0.390981696
	Wind Speed (mps) for Winter 2	ww2	1.785714	0.301471	0.733518818	0.378071741
	Cloud Coverage (Octs) for Winter 1	cw1	2.195455	0.583824	1.224426841	0.317740336
	Cloud Coverage (Octs) for Summer	cs	3.994624	2.467816	3.230804227	0.334672995
	Cloud Coverage (Octs) for Monsoon	cm	5.880606	4.795172	5.328688682	0.236753138
	Cloud Coverage (Octs) for Winter 2	cw2	2.3	0.632292	1.447604068	0.360374434
	Flood Affected Area (%)	f	68	0	17.52045455	15.13481401
	Earthquake Count	ec	3	0	0.25	0.61474139
	Average Earthquake Magnitude (Richter Scale)	em	6.8	0	0.985454545	2.153268424
	Cyclone Count	cc	1	0	0.136363636	0.347141757
	Drought Count	dc	1	0	0.204545455	0.408032457
Response	AMON Rice (Lac M. ton)	amon	130.23	55.87	90.02772727	21.01417128
	AUS Rice (Lac M. ton)	aus	32.88	11.16	23.11954545	6.062918537
	Boro Rice (Lac M. ton)	boro	190.07	16.5	81.81522727	58.86766137
	Jute (Lac Bales)	jute	83.96	35.3	52.02409091	11.15013512
	Potato (Lac M. ton)	potato	89.5	4.55	25.85363636	25.23384246
	Wheat (Lac M. ton)	wheat	19.08	0.895	9.981113636	5.054057183

The final set of data collected is represented in Table 1. The data is divided into two parts, Predictor and Response to represent the weather parameters and crop yields respectively. Units of measurement for each of the data are added with the name. Acronyms for all the data are provided, referencing their uses in later sections. Furthermore, the maximum (Max), minimum (Min), average (Mean) and standard deviation (Sd) are provided for each data to better understand the distribution and nature of the data.

3.2. Feature Selection & Preprocessing

After data collection, the attributes were verified to be appropriate for linear regression. There are six problems that can occur when fitting a linear regression model to a dataset [1]. These are:

1. Non-linearity of the response-predictor relationships
2. Correlation of error terms, environment.
3. Non-constant variance of error terms,
4. Outliers,
5. High-leverage points and
6. Collinearity.

To detect whether these problems are present in the dataset, residual plots and the Pearson correlation coefficients were used. The residual plots revealed outliers in the data which span the years 2009 to 2013. These years were removed from the data to get a more accurate and correct prediction. The Pearson correlation coefficients displayed in Figure 1 shows the absence of any major collinearity between the features.

Table 2: P Statistics of the Data

Attribute	p value					
	AMON	AUS	BORO	Jute	Potato	Wheat
Temperature (C) for Winter 1	0.90383	0.65448	0.06662	0.35561	0.36695	0.35856
Temperature (C) for Summer	0.11543	0.68052	0.16660	0.89832	0.19260	0.43537
Temperature (C) for Monsoon	0.21804	0.86918	0.81732	0.63262	0.20482	0.09189
Temperature (C) for Winter 2	0.42799	0.48903	0.03119*	0.09010	0.91773	0.32762
Rainfall (mm) for Winter 1	0.34632	0.51863	0.28337	0.66514	0.31909	0.44916
Rainfall (mm) for Summer	0.22911	0.19986	0.75106	0.15713	0.88048	0.76722
Rainfall (mm) for Monsoon	0.56167	0.46355	0.01187*	0.07394	0.67539	0.76346
Rainfall (mm) for Winter 2	0.15973	0.18468	0.07202	0.91752	0.72353	0.39209
Relative Humidity (%) for Winter 1	0.24310	0.62125	0.01383*	0.12375	0.70651	0.81304
Relative Humidity (%) for Summer	0.0343*	0.69420	0.41432	0.17518	0.50731	0.0456*
Relative Humidity (%) for Monsoon	0.35996	0.41247	0.01174*	0.71048	0.88614	0.14667
Relative Humidity (%) for Winter 2	0.53789	0.42076	0.01958*	0.99512	0.46641	0.26078
Bright Sunshine (Hours) for Winter 1	0.58769	0.61021	0.04643*	0.17399	0.82073	0.43093
Bright Sunshine (Hours) for Summer	0.50066	0.66527	0.80347	0.89943	0.89301	0.01534*
Bright Sunshine (Hours) for Monsoon	0.14649	0.81077	0.18866	0.09585	0.30261	0.44581
Bright Sunshine (Hours) for Winter 2	0.01729*	0.34810	0.35856	0.51723	0.49250	0.44049
Wind Speed (mps) for Winter 1	0.01637*	0.73061	0.39827	0.29641	0.21281	0.58530
Wind Speed (mps) for Summer	0.17325	0.61110	0.23297	0.55640	0.87657	0.56192
Wind Speed (mps) for Monsoon	0.00637*	0.85077	0.00137*	0.76162	0.01461*	0.58958
Wind Speed (mps) for Winter 2	0.21764	0.56888	0.82586	0.90522	0.50158	0.63259
Cloud Coverage (Octs) for Winter 1	0.45996	0.44393	0.15546	0.10160	0.69365	0.43277
Cloud Coverage (Octs) for Summer	0.19032	0.93512	0.33466	0.80715	0.28042	0.02354*
Cloud Coverage (Octs) for Monsoon	0.07781	0.29442	0.0006*	0.05377	0.03923*	0.17725
Cloud Coverage (Octs) for Winter 2	0.01902*	0.90968	0.01046*	0.29249	0.37746	0.73560
Flood Affected Area (%)	0.04862*	0.13737	0.70862	0.49346	0.97069	0.68621
Earthquake Count	0.39671	0.19153	0.10491	0.80805	0.10790	0.87668
Average Earthquake Magnitude (Richter Scale)	0.21974	0.42970	0.26360	0.42883	0.26842	0.81989
Cyclone Count	0.96394	0.34943	0.32774	0.09580	0.21275	0.62332
Drought Count	0.06621	0.80020	0.04877*	0.25060	0.08666	0.80999

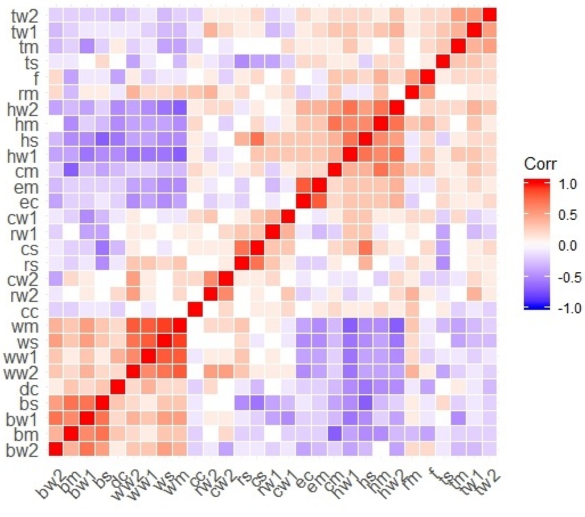

Figure 1: Pearson correlation of the Features

After validating the data for regression, features were verified with T-testing. Using T-test, p-values of the attributes were calculated for each crops. Only features with a p-value less than 0.05 were accepted as features significant enough to predict production. The final list of features for each crops is shown in Table 2. It is seen that the crops AUS rice and Jute have no significant attribute for prediction, which means no weather parameter can correctly predict the production of these two crops. Therefore these two crops were removed from further testing. Lastly, the attributes are standardized. Standardization is necessary because the features are calculated in different scales.

3.3. Modeling

The final dataset for the four crops was used in six different learning algorithms – Linear Regression,

Table 3: Coefficients of Linear Regression Analysis

Crop	Attribute	Coefficient	Std. Error	T Value
Amon	Relative Humidity (%) for Summer	1.8051	0.5944	3.0368
	Bright Sunshine (Hours) for Winter 2	-10.2855	2.1643	-4.7523
	Wind Speed (mps) for Winter 1	44.1825	15.6506	2.8231
	Wind Speed (mps) for Monsoon	-45.513	9.2178	-4.9375
	Cloud Coverage (Octs) for Winter 2	-14.6428	3.8644	-3.7892
	Flood Affected Area (%)	-0.2244	0.0787	-2.8501
	(Const)	86.7998	51.6543	1.6804
Boro	Temperature (C) for Winter 2	4.3946	8.9097	0.4932
	Rainfall (mm) for Monsoon	0.0141	0.1103	0.1282
	Relative Humidity (%) for Winter 1	-1.0663	2.776	-0.3841
	Relative Humidity (%) for Monsoon	-7.0831	13.2921	-0.5329
	Relative Humidity (%) for Winter 2	3.4543	4.2846	0.8062
	Bright Sunshine (Hours) for Winter 1	-13.5155	7.0718	-1.9112
	Wind Speed (mps) for Monsoon	-128.1822	31.9833	-4.0078
	Cloud Coverage (Octs) for Monsoon	46.0634	27.9839	1.6461
	Cloud Coverage (Octs) for Winter 2	-16.974	16.2109	-1.0471
	Drought Count	-3.772	13.9479	-0.2704
	(Const)	465.1046	963.4549	0.4827
Potato	Wind Speed (mps) for Monsoon	-43.1239	5.9285	-7.274
	Cloud Coverage (Octs) for Monsoon	14.0192	5.9444	2.3584
	(Const)	8.0418	35.126	0.2289
Wheat	Relative Humidity (%) for Summer	0.8947	0.3684	2.4288
	Bright Sunshine (Hours) for Summer	-7.8673	1.4017	-5.6125
	Cloud Coverage (Octs) for Summer	-11.7719	2.3931	-4.9191
	(Const)	41.5285	32.0684	1.295

Random Forest, KNN Regression, Decision Tree, Support Vector Machine, and Zero-R. For training the data, K fold cross validation technique was used with k=10.

Among the six algorithms used to derive models, comparison was conducted to decide on the best fit for prediction. This was done by performing Paired T-test and comparing Root Mean Squared Errors (RMSE).

4. Experimental Analysis

After successfully performing the testing, the findings of the analysis were compiled.

4.1. Inference

A major part of this report was to infer how weather effects the production of crops in Bangladesh. With that target, the coefficients for all the accepted features were calculated from the initial T-test. The coefficients for each attribute for each of the four crops are displayed in Table 3. From this table, one can derive exactly how much a climate parameter influences crop production.

The following statement can be applied to the findings to better represent it to the general populace on the effects of weather on crop yields: "Increase in X by 1 U in the year A will increase/decrease the annual production of crop Y by y lac metric ton in the fiscal year of A to $(A + 1)$; where X = attribute name, U = attribute's unit, A = year, Y = crop name and y = coefficient of X for Y."

For instance, for the crop Amon, it can be stated that, increase in Relative Humidity for Summer (March-June) by 1% in the year 2018 will increase the annual production of Amon by approximately 1.8051 lac metric ton in the fiscal year of 2018-19.

The same can be said for instances where the weather takes a negative effect on crop production. For example, for the crop Boro, it can be stated that, increase in Relative Humidity for the 1st Winter (January-February) by 1% in the year 2018 will decrease the annual production of Boro by approximately 1.0663 lac metric ton in the fiscal year of 2018-19.

The approximations are based on the coefficients derived from a linear regression analysis of all the significant weather parameters for the given crops. In a practi-

Table 4: RMSE (* indicates statistically significant at 0.05 level compared to ZeroR)

Crop	ZeroR	Linear Regression	Support Vector	KNN	REPTree	Random Forest
Amon	16.85	7.41 *	7.67 *	9.00 *	13.3	9.77 *
Boro	49.83	18.22 *	20.58 *	27.33 *	30.57 *	23.70 *
Potato	13.51	7.73 *	7.47 *	7.63 *	10.42	8.76 *
Wheat	5.23	3.22 *	3.58 *	3.93 *	4.55	3.91 *

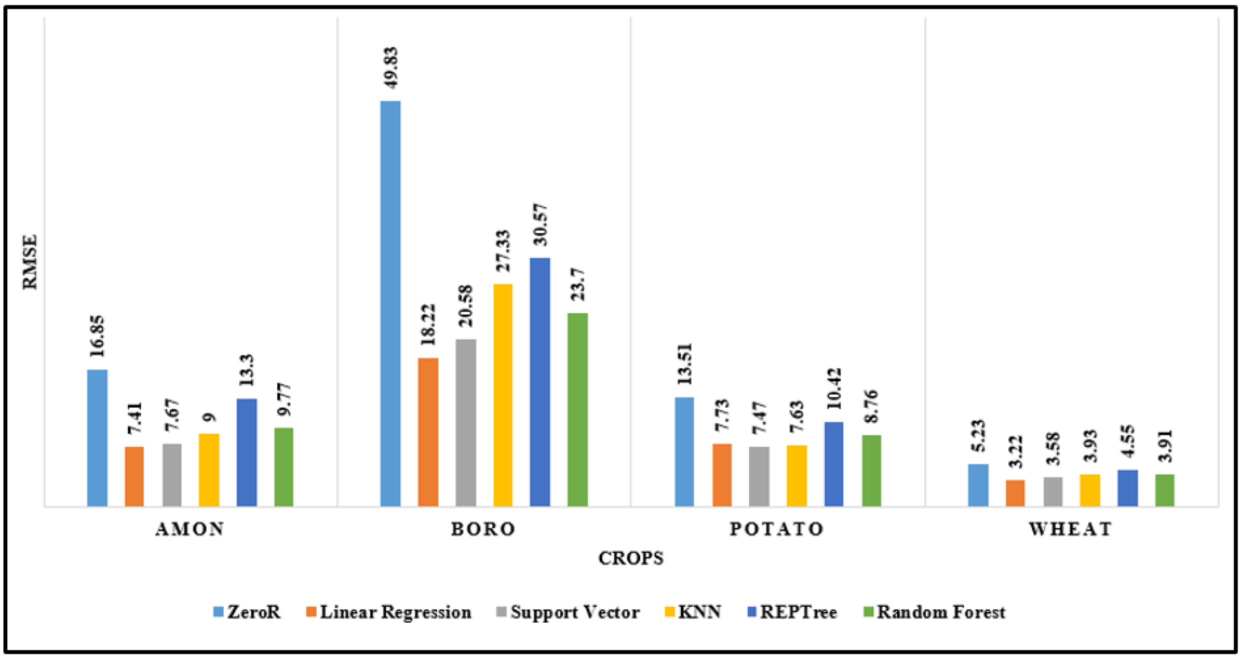

Figure 2: RMSE comparison of different prediction models

cal scenario, it may not produce the exact result. Nevertheless, it is a useful tool in understanding how a single weather pattern or multiple patterns together can affect a crop's production. It can also provide estimations of the year's crop production solely based on the weather parameters.

4.2. Prediction

Six different prediction algorithms were used to create prediction models for the four different crops. A paired T-test was performed on the test results. The different models were compared on the basis of Root Mean Squared Error (RMSE), the results displayed in Table 4. The table also states the models that have the capability to provide significantly accurate results.

For instance, in the case of the crop Amon, it can be seen that the models ZeroR and Decision Tree (REPTree) have a higher rate of RMSE, hence these are deemed insignificant in predicting the production of Amon. On the other hand, models Linear Regression, Support Vector Machine, KNN and Random Forest are all marked as statistically significant for prediction because of their comparatively low RMSE. Among these, Linear Regression has the least RMSE: 7.41, closely followed by Support Vector Machine: 7.67. Therefore, for predicting the production of Amon rice, Linear Regression is the preferred model.

Similarly, the best prediction models for all the four crops can be derived by choosing the model with the least RMSE, which we can see in Figure 2. The models best fit for each of the crops are:

1. AMON rice: Linear Regression
2. BORO rice: Linear Regression
3. Wheat: Linear Regression
4. Potato: Support Vector Machine

5. Conclusion

This paper demonstrates the effects of different weather parameters on the production of various crops in Bangladesh. It was derived how much variation in the considered weather elements can individually influence the annual crop yields of the six main crops of Bangladesh. Alongside this, prediction models were built based on the weather parameters. Later these were statistically compared to find the best fits. Separate prediction models were chosen to best estimate the production of the four crops at the end of a fiscal year based on appropriate seasonal predictors of the weather from the year before. The inference model derived can be used as an easy interpretation medium for the general people to understand the direct effects of different climate parameters. The prediction models can be a great asset for estimating yearly crop yields based solely on weather data. These findings can be deftly used to directly or indirectly assist the country's agricultural and economic advancement.

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