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A Machine Learning influenced Recommendation System for Predicting the Rainfall and Price for Crops in Badulla District

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***Abstract*— Every day, agriculture becomes more vital to the global economy. Daily population expansion necessitates substantial crop output for human existence. But as the population has increased, human activity has also altered the environment. Therefore, it has resulted in challenges with weather forecasting, which is crucial for crop planting in the agricultural sector. Thus, the globe needs a method to forecast agrarian weather. In addition, it is highly advantageous for farmers to understand the production rate they can achieve and the price range they may expect for their efforts. As a result, Machine learning technologies have become unique and fashionable in the agricultural industry due to their ability to provide accurate farming predictions. Selecting suitable plants for planting has evolved into a necessity. This study focuses on the application of machine learning to estimate the optimal crop for a given period. In this work, the author addresses the beginning part of the study: precipitation prediction under the weather forecast and pricing forecast. The authors have employed six distinct machine-learning models to forecast rainfall and crop prices.**

Keywords—Machine Learning, Weather Prediction, Price Prediction, Crop Prediction, XGBoost

I. Introduction

Food is a necessity for humans, like water. All living things require water to survive. Before the agricultural period, all humans obtained sustenance by hunting animals. People began cultivating food crops around 11,500 years ago after discovering that roots and crops were suitable for human consumption. From then on, agriculture became the primary source of income for most people [1]. The majority of agricultural advancements and fresh discoveries have subsequently propelled the agricultural sector. Thus, agriculture is the art and science of cultivating crops using soil and other inputs and raising livestock [2]. Then, in most nations, the agricultural sector becomes one of the most important economic sectors with rapid economic growth and the answer to global food insecurity [3, 4].

In the prehistoric era of agriculture, where technology was not a big part, most crop diseases were identified by the human naked eye [5]. However, the precision and accuracy of their decision were inferior. However, due to the high demand for food due to rapid population growth, food production should be inadequate for human consumption. Therefore, most farmers strive to increase crop production within a short period with a minimum loss [6-8].

Between 30 and 50 % of food and crops are wasted before consumption. In addition, due to fast population development, fertile ground for agricultural production is restricted, and environmental contamination has caused an increase in illnesses and a decrease in yield [9]. Consequently, the majority of farmers must cultivate their crops with inadequate resources. As a result, most of them have attempted to develop novel cultivation techniques. Selecting a food crop fit for the chosen agri-zone is one of the most effective techniques to boost crop yield with few resources and illnesses. However, this is contingent upon market pricing, government regulations, and the production pace. Numerous aspects, including soil classification, production rate, weather forecasting, and crop classification, should be considered when identifying acceptable crop types. However, it isn't easy to remember and anticipate meteorological conditions in advance [10]. Before picking an appropriate crop type, it is crucial to ascertain the environmental conditions.

People are more likely to use modern farming technologies to find new solutions to these issues. They commonly use machines to automate manual tasks. Gene modification hybridization was used to improve the quality of the crops [11]. Machine Learning arose as a result of advancements in ICT.

Machine learning employs algorithms for which only soft coding is necessary. In the process, algorithms begin to self-learn, utilizing pertinent data. Their performance to do a certain activity improves as they develop and gain expertise. According to their data labeling, machine learning in nature may be divided into three subcategories. There are three types of learning: unsupervised, supervised, and semi-supervised. Consideration of supervised learning necessitates labeled data for object identification and discrimination.

Random Forest, KNN, Regression, and Decision Tree are some examples of supervised learning. As the name implies, it uses unlabeled data and clustering populations in different groups when considering unsupervised data. K-Means and Apriori algorithms are an example of unsupervised learning. Both labeled and unlabeled data are used in semi-supervised learning. This technology is used in computer vision, pattern recognition, spacecraft engineering, biology, and finance [12]. So, machine learning has good advantages for the agricultural sector. Therefore, machine learning can be beneficial for predicting yield rate, soil classification, weather prediction, and crop classification.

Looking back at the history of the agricultural sector in Sri Lanka, it was the most affluent sector. However, the agricultural sector's Gross Domestic Product (GDP) has not improved significantly. In 2009, the GDP was 12.69%; by 2020, it was 7.3%, a decline of 5.39 % (https://tradingeconomics.com/sri-lanka/gdp). However, Sri Lanka flourished with abundant natural resources for agricultural production. Models of machine learning can be utilized to empower the industry. This study aims to discover a solution by employing machine learning to forecast the optimal crop variety for a certain period in the region of Badulla.

After this study, a crop recommendation system based on weather, price, and yield will be created. In this work, the authors report the initial phase of their study, which focuses on predicting rainfall and agricultural prices. Six machine learning methods were selected based on a comprehensive review of the literature and the advice of industry experts: Decision Tree Regression, Support Vector Regression (SVR), Artificial Neural Network (ANN), Random Forest Regression, Recurrent Neural Network (RNN), and XGBoost. The optimal machine-learning algorithm for each component will be chosen to construct the final machine-learning model.

The remainder of the paper is structured as follows. Related works are explained in Section II, while the detailed methodology is described in Section III. Section IV focuses on results and discussions. Finally, Section V concludes the paper with a future direction.

II. Related Works

Jain and Ramesh [13] have proposed a method for selecting crops based on soil parameters and weather prediction. It also helps to maximize the crop yield based on soil and weather. Also, this study provides sowing time for the crops based on seasonal weather forecasting. Weather prediction is made by using RNN. For crop selection, they used the Random Forest classification algorithm. Finally, they compared the results using ANN to get better accuracy.

Bang, et al. [14] used fuzzy logic techniques to predict crop yield using rainfall and temperature parameters. ARMAX (ARMA Max) and Seasonal Auto-Regressive Integrated Moving Average (SARIMA) models predicted temperature. Also, Auto Regressive Moving Average (ARMA) and ARMAX models were used to predict rainfall. Also, the ARMAX model predicts other factors, such as temperature, cloud cover, and evapotranspiration. Finally, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) is calculated to find the model's accuracy. Then crop yield was predicted using the fuzzy inference system based on the two parameters.

Singh, et al. [15] presented a system with low cost, reliability, and efficiency for weather forecasting. As the language, they have used Python on the Raspberry Pi board. The Random Forest classification algorithm has been used for this. Parmar, et al. [16] reviewed different methods to predict rainfall. Also, give the idea of the problem that might happen when applying these methods for forecasting. Finally, they have suggested most suitable approach is using an Artificial Neural Network.

Gamage and Kasthurirathna [17], this paper provide a method to make profitable vegetable farming in Sri Lanka. They have used Deep Learning, Machine Learning, and Visualization as the key technologies. A mobile application has also been developed as the product of this research. This paper has used Long Short-Term Memory (LSTM) for vegetable prediction and ARIMA for price prediction. So, as the final result, this application helps farmers choose suitable crops to be planted and gain maximum profit for a selected area.

In the research by Ridwan, et al. [18], the rainfall data in Tasik Kenyir, Terengganu. This work mainly focuses on two approaches for predicting rainfall: (i) forecasting rainfall depending on historical rainfall data using the Autocorrelation Function (ACF) and (ii) forecasting rainfall depending on projected and historical rainfall data using the Projected Error. Both techniques use various algorithms to find the best rainfall forecast for different time horizons, such as BDTR, NNR, DFR, and BLR. The coefficient of determination, R2, has been used to measure the performance.

In Basha, et al. [19], The Auto-encoder Neural Network and Multilayer Perceptron were used in this study to demonstrate the Deep Learning Approach for predicting rainfall. To measure the accuracy of these models, they used MSE and RMSE. Also, This research looked at the various methodologies used to forecast and predict rainfall and the problems that can arise when using different ways to forecast rainfall.

Abdel-Kader, et al. [20], This paper describe a hybrid approach for forecasting rainfall that combines Multi-Layer Perceptron (MLP), which is a common type of Feed Forward Neural Network (FFNN), with Particle Swarm Optimization (PSO). The integration of PSO with MLP isn't only for forecasting rainfall but also to enhance the performance of the network, as seen by comparisons with other Back Propagation (BP) algorithms like Levenberg-Marquardt (LM) and Root Mean Square Error (RMSE). In this proposed technique, In the first step, a neural network is built by determining the number of neurons for the input layer, output layer, and hidden layer; in the second step, PSO is mainly employed for the automatic synthesis of optimum weights that were used in the first phase for training the network

III. Methodology

In this paper, the authors discuss the initial phase of the study. Rainfall and price prediction were focused on using six different machine learning models. The procedure that was used is shown in Fig 1.

A. Crop Selection

Badulla District is an agricultural district divided into upper and lower regions with climatic, topographical, and geographic differences, with the upper region notable for vegetable and tea cultivation. The authors selected seven primary vegetables based on the extent of cultivation and production data to focus our research on areas of relevance because our objective is to study rainfall and price prediction for the most popular vegetables grown in the Badulla District.

Beans, tomato, cabbage, carrot, brinjal, and leeks crops were the main vegetable crops based on the greatest cultivation extent and production data (Table 1) from the Department of Census and Statistics. The authors considered the 2001 to 2020 data on the crops. Due to space limitations, Table I shows the sample data between 2001 to 2005

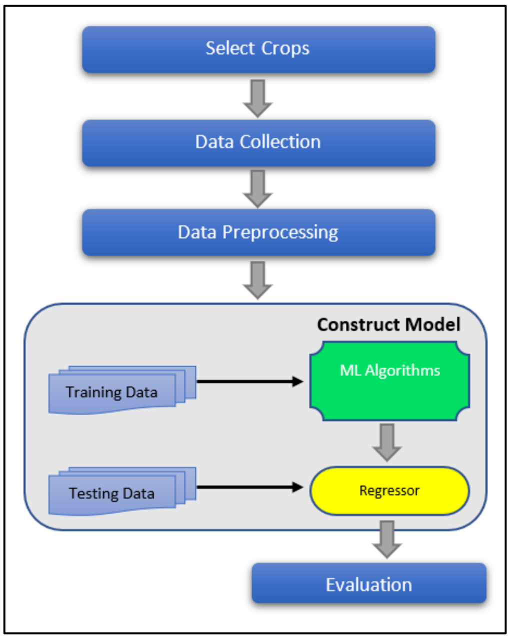


Fig. 1. The Approach of the 1st Step

B. Data Collection

For the study, first, the rainfall data was collected from the Badulla agricultural station (Station ID: 43479). The authors were able to collect data from 2002 to 2017. Fig 2 shows the collected sample rainfall data. Then the price data of selected crops were collected from the official website of the Central bank of Sri Lanka. Fig 3 shows the collected crop price data.

C. Data Preprocessing

Data preprocessing is one of the main parts of any research. This step extracts the data to be analyzed from the original data set. Separate excel sheets for each factor were created manually. The excel sheets with the day and value for the rainfall and price were created. The authors wanted to make the daily prediction for the study. The authors must handle the missing data, remove unnecessary data, and so on. Otherwise, it will not be able to get the expected quality result.

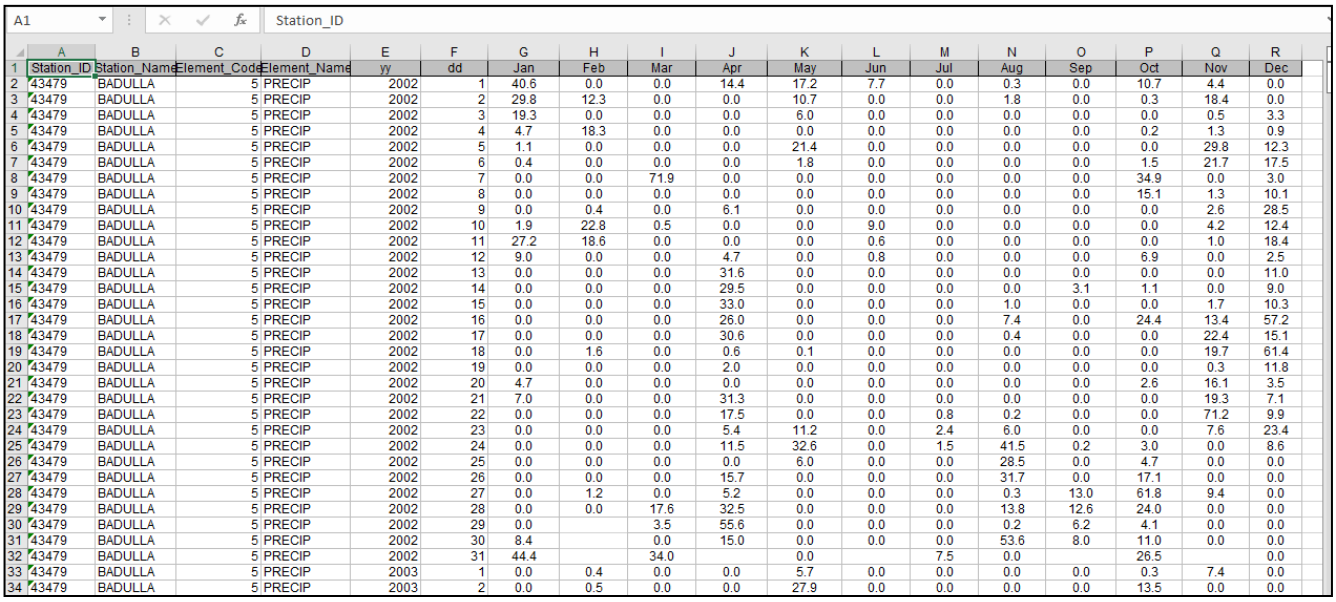
For all models, the authors use 80% for the training and 20% for the testing purpose of our data. Here, we could find only a few raw data with rainfall and price when dealing with the missing data. So, we use the “interpolate ()” method in the Pandas Date Frame library. Here, in Python, interpolation is a method for estimating unknown data points between two known data points. When preparing data, interpolation is commonly used to fill in missing values in a data frame or series. Regarding the SVR model, we used the feature scaling method to get all feature values and dependent values between -3 to +3.

D. Constructing Models

After manually creating the data file we wanted to continue the research, we chose six models for this study. They are (i) Random Forest regression, (ii) SVR, (iii) Decision Tree regression, (iv) ANN, (v) RNN and (vi) XGBoost.

TABLE I. EXTEND AND PRODUCTION DATA OF SELECTED CROPS (2001 - 2005)

Year	Bean		Tomatoes		Cabbage		Brinjal		Leeks		Carrots	
	Extend	*Production*	*Extend*	*Production*	*Extend*	*Production*	*Extend*	*Production*	*Extend*	*Production*	*Extend*	*Production*
2001	2,721	15,811	1,354	12,799	1,177	21,822	1,010	10,043	242	2,255	693	7,225
2002	2,639	15,883	1,330	13,158	1,155	21,740	990	9,851	240	2,266	687	7,263
2003	2,822	16,984	1,539	15,560	1,390	26,059	1,137	11,507	218	2,340	738	8,092
2004	3,663	25,946	1,669	17,965	1,311	22,669	1,000	12,598	192	2,424	709	8,974
2005	3,644	24,472	1,633	17,568	1,215	21,014	1,051	13,054	168	2,036	715	9,002



A1 Station_ID

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Station_ID	Station_Name	Element_Code	Element_Name	yy	dd	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2	43479	BADULLA	5	PRECIP	2002	1	40.6	0.0	0.0	14.4	17.2	7.7	0.0	0.3	0.0	10.7	4.4	0.0
3	43479	BADULLA	5	PRECIP	2002	2	29.8	12.3	0.0	0.0	10.7	0.0	0.0	1.8	0.0	0.3	18.4	0.0
4	43479	BADULLA	5	PRECIP	2002	3	19.3	0.0	0.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	0.5	3.3
5	43479	BADULLA	5	PRECIP	2002	4	4.7	18.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	1.3	0.9
6	43479	BADULLA	5	PRECIP	2002	5	1.1	0.0	0.0	0.0	21.4	0.0	0.0	0.0	0.0	0.0	29.8	12.3
7	43479	BADULLA	5	PRECIP	2002	6	0.4	0.0	0.0	0.0	1.8	0.0	0.0	0.0	0.0	1.5	21.7	17.5
8	43479	BADULLA	5	PRECIP	2002	7	0.0	0.0	71.9	0.0	0.0	0.0	0.0	0.0	0.0	34.9	0.0	3.0
9	43479	BADULLA	5	PRECIP	2002	8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	15.1	1.3	10.1
10	43479	BADULLA	5	PRECIP	2002	9	0.0	0.4	0.0	6.1	0.0	0.0	0.0	0.0	0.0	0.0	2.6	28.5
11	43479	BADULLA	5	PRECIP	2002	10	1.9	22.8	0.5	0.0	0.0	9.0	0.0	0.0	0.0	0.0	4.2	12.4
12	43479	BADULLA	5	PRECIP	2002	11	27.2	18.6	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	1.0	18.4
13	43479	BADULLA	5	PRECIP	2002	12	9.0	0.0	0.0	4.7	0.0	0.8	0.0	0.0	0.0	6.9	0.0	2.5
14	43479	BADULLA	5	PRECIP	2002	13	0.0	0.0	0.0	31.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.0
15	43479	BADULLA	5	PRECIP	2002	14	0.0	0.0	0.0	29.5	0.0	0.0	0.0	0.0	3.1	1.1	0.0	9.0
16	43479	BADULLA	5	PRECIP	2002	15	0.0	0.0	0.0	33.0	0.0	0.0	0.0	1.0	0.0	0.0	1.7	10.3
17	43479	BADULLA	5	PRECIP	2002	16	0.0	0.0	0.0	26.0	0.0	0.0	0.0	7.4	0.0	24.4	13.4	57.2
18	43479	BADULLA	5	PRECIP	2002	17	0.0	0.0	0.0	30.6	0.0	0.0	0.0	0.4	0.0	0.0	22.4	15.1
19	43479	BADULLA	5	PRECIP	2002	18	0.0	1.6	0.0	0.6	0.1	0.0	0.0	0.0	0.0	0.0	19.7	61.4
20	43479	BADULLA	5	PRECIP	2002	19	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	11.8
21	43479	BADULLA	5	PRECIP	2002	20	4.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.6	16.1	3.5
22	43479	BADULLA	5	PRECIP	2002	21	7.0	0.0	0.0	31.3	0.0	0.0	0.0	0.0	0.0	0.0	19.3	7.1
23	43479	BADULLA	5	PRECIP	2002	22	0.0	0.0	0.0	17.5	0.0	0.0	0.8	0.2	0.0	0.0	71.2	9.9
24	43479	BADULLA	5	PRECIP	2002	23	0.0	0.0	0.0	5.4	11.2	0.0	2.4	6.0	0.0	0.0	7.6	23.4
25	43479	BADULLA	5	PRECIP	2002	24	0.0	0.0	0.0	11.5	32.6	0.0	1.5	41.5	0.2	3.0	0.0	8.6
26	43479	BADULLA	5	PRECIP	2002	25	0.0	0.0	0.0	0.0	6.0	0.0	0.0	28.5	0.0	4.7	0.0	0.0
27	43479	BADULLA	5	PRECIP	2002	26	0.0	0.0	0.0	15.7	0.0	0.0	0.0	31.7	0.0	17.1	0.0	0.0
28	43479	BADULLA	5	PRECIP	2002	27	0.0	1.2	0.0	5.2	0.0	0.0	0.0	0.3	13.0	61.8	9.4	0.0
29	43479	BADULLA	5	PRECIP	2002	28	0.0	0.0	17.6	32.5	0.0	0.0	0.0	13.8	12.6	24.0	0.0	0.0
30	43479	BADULLA	5	PRECIP	2002	29	0.0		3.5	55.6	0.0	0.0	0.0	0.2	6.2	4.1	0.0	0.0
31	43479	BADULLA	5	PRECIP	2002	30	8.4		0.0	15.0	0.0	0.0	0.0	53.6	8.0	11.0	0.0	0.0
32	43479	BADULLA	5	PRECIP	2002	31	44.4		34.0		0.0		7.5	0.0		26.5		0.0
33	43479	BADULLA	5	PRECIP	2003	1	0.0	0.4	0.0	0.0	5.7	0.0	0.0	0.0	0.0	0.3	7.4	0.0
34	43479	BADULLA	5	PRECIP	2003	2	0.0	0.5	0.0	0.0	27.9	0.0	0.0	0.0	0.0	13.5	0.0	0.0

Fig. 2. Screenshot of Collected Rainfall Data

	A	B	C	D	E	F	G
1	Date	Green bean	Tomatoe	Cabbage	Brinjals	Leeks	Carrot
2	1/1/1985	9.1	10.04	6.78	6.66	8.87	9.33
3	2/1/1985	7.69	9.17	5.15	5.97	13.59	9.77
4	3/1/1985	6.91	10.16	5.76	5.76	8.21	10.44
5	4/1/1985	8.74	10.83	4.89	6.64	8.82	12.61
6	5/1/1985	13.26	15.67	10.72	9.11	12.19	15.39
7	6/1/1985	16.55	21.01	9.5	10.02	13.07	15.53
8	7/1/1985	11.98	13.88	9.55	9.4	12.01	12.09
9	8/1/1985	9.95	8.81	10.35	8.92	10.55	10.4
10	9/1/1985	7.11	6.39	7.77	7.41	8.46	7.67
11	10/1/1985	7.08	7.58	6.66	7.25	8.67	7.16
12	11/1/1985	9.81	10.76	7.98	9.66	10.26	8.63
13	12/1/1985	10.32	17.34	9.58	11.09	11.64	10.96
14	1/1/1986	13.13	20.64	10.13	10.36	13.84	16.21
15	2/1/1986	14.51	19.22	11.55	11.3	14.27	18.14
16	3/1/1986	14	20.78	9.23	8.56	13.59	14.7
17	4/1/1986	9.23	15.13	10.49	8.8	13.31	12.77
18	5/1/1986	11.16	12.92	8.71	8.6	14.69	13.64
19	6/1/1986	14.75	13.44	8.85	9.84	16.53	15.56
20	7/1/1986	13.92	13.1	7.98	9.04	14.13	16.5

Fig. 3. Collected Crop Price Data

Since we have to predict the continuous values, we chose the regression model instead of the classification model.

1) Decision Tree Regression

The decision tree is the most widely used and beneficial for supervised learning. It is used to resolve classification and regression problems, albeit later became widely used.

2) Random Forest Regression

Random Forest is another algorithm that makes judgments based on the quality aspects of many Decision Trees. It is a Tree-based algorithm. The Random Forest approach is faster and more reliable than alternative regression models.

3) SVR

SVR is a supervised learning method for predicting discrete values. The same technique as SVMs is used in SVR.

4) ANN

ANNs have recently gained much attention in many areas, such as engineering, medical science, and economics. Neurons, the fundamental brain processing organ, are associated with several thousand other neurons, like a typical neuron.

5) RNN

LSTM network is an advanced version of RNN. This network enables to recall of information from the past straightforward way. The vanishing gradient problem of RNN is overcome here. The authors used LSTM for the prediction.

6) XGBoost Regressor

XGBoost is a decision-tree-based and gradient-boosting-based ensemble Machine Learning technology. ANNs are better than all other frameworks and algorithms for anticipating problems involving unstructured data like text, pictures, etc. Decision tree-based algorithms are considered the best models for small-to-medium structured or tabular data.

Here, we wanted to find the best model parameter for more accuracy and performance. In that case, we use the GridSearchCV method for the parameter tuning process. Here, we used the cross-validation value as the 10 (cv=10). This method was applied to all models for parameter tuning except RNN (LSTM) and ANN. Regarding the ANN model, we used two hidden layers with six nodes for each. As the activation function, we used the “Relu function.” Also, we use batch size as the 32 and 100 epochs when training the model.

IV. RESULTS AND DISCUSSION

Here, we mainly predict the rainfall and price. So, we work with continuous values. So, our study works with qualitative data. First, we check the plots’ rainfall and price data. Fig 4 shows the rainfall data plot.

Then with the Statmodels library in Python, we checked four things. They are (i) observed data, (ii) trends, (iii) seasonal patterns, and (iv) residual data. Fig 5 and Fig 6 show the rainfall data decompose and price data decompose, respectively.

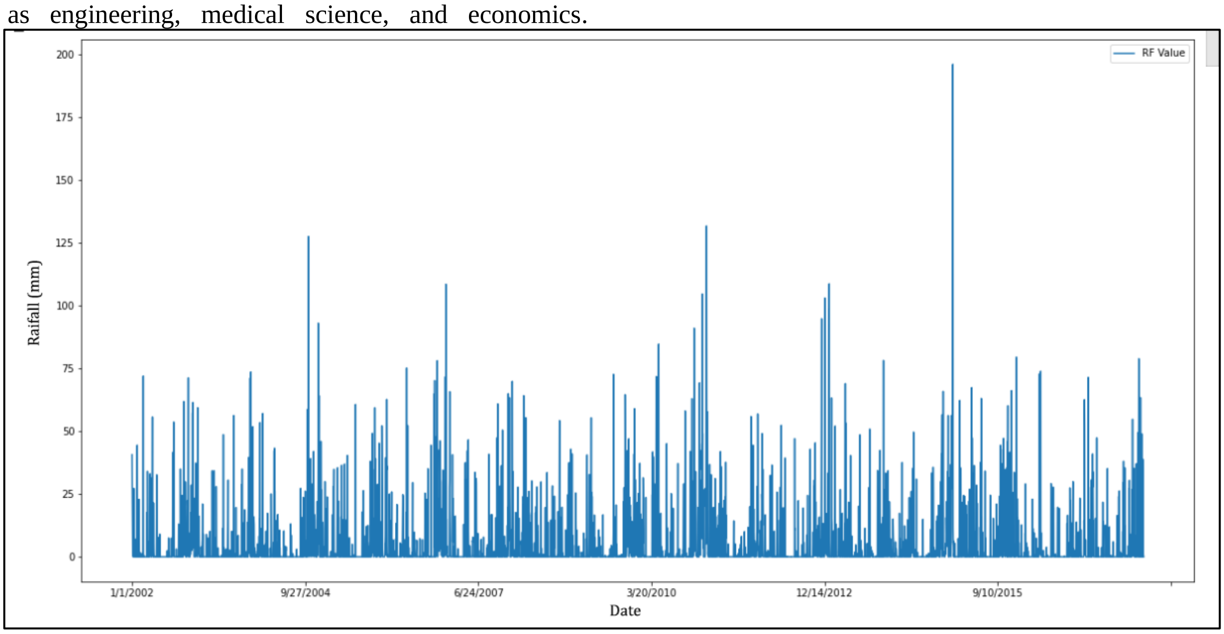


Fig. 4. Rainfall Data Plot

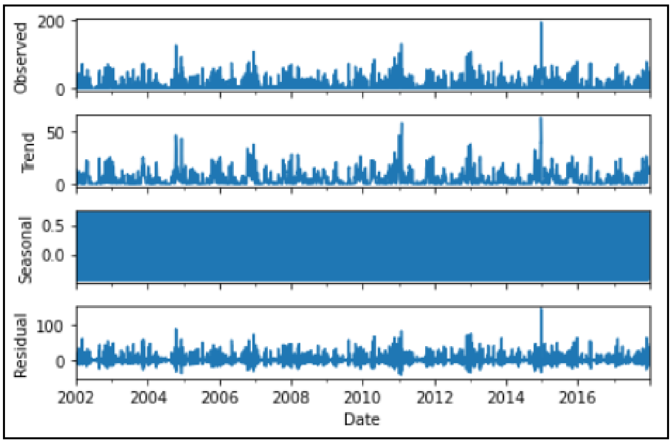


Fig. 5. Rainfall Data Decompose

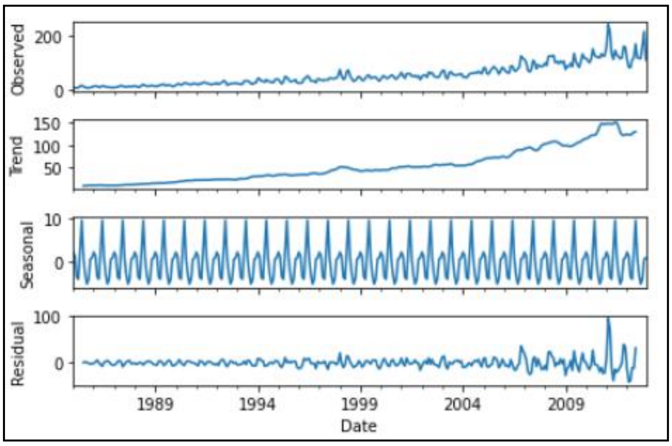


Fig. 6. Price Data Decompose

We measured each model's performance with the R squared and RMSE values. The below tables will show the results that we got from these models. In our case, if R-value is closer to 1, the model has good accuracy. The authors considered a good accuracy if the RMSE value is below ten or closer to 10. Table II and Table III show the rainfall and price predictions obtained, respectively.

TABLE II. FINAL RESULT OF RAINFALL PREDICTION

	Decision Tree	**Random Forest**	**SVR**	**ANN**	**RNN**	**XGBoost**
RMSE Value	12.07	11.84	12.46	11.97	14.12	11.59
R-Value	0.03	0.07	-0.03	0.05	0.51	0.11

TABLE III. FINAL RESULT OF PRICE PREDICTION

	Decision Tree	**Random Forest**	**SVR**	**ANN**	**RNN**	**XGBoost**
RMSE Value	13.12	10.58	9.76	11.22	71.54	11.38
R-Value	0.88	0.92	0.93	0.91	-3.39	0.91

As the study shows, with rainfall prediction, XGBoost is the best model that suits the forecast. In Fig 4 and Fig 5, it can be clearly seen that the rainfall data had a very messy structure with no proper trend or seasonal pattern. So, XGBoost was capable of dealing with that kind of structure. The price prediction showed the best accuracy compared to the rainfall prediction. It could be seen that the raw data structure of the price has made a considerable impact on increasing these performances. So, in our case, SVR algorithms have shown the best performance with this kind of data structure.

V. CONCLUSION AND FUTURE WORKS

This study uses a machine learning model to pick viable crops in Sri Lanka's Badulla District for a certain period. This article addresses the first phase of the investigation, which involves forecasting rainfall and prices. This study evaluated six distinct models: Decision Tree Regression, Random Forest Regression, ANN, RNN, and XGBoost. For each prediction, high-performance methods are selected from among these options. Consequently, XGBoost had the highest performance for predicting precipitation, whereas SVR demonstrated the best performance for predicting prices. The performance was measured using the root-mean-square error (RMSE) and R square value for the coefficient of determination.

This paper provides a good platform for future research. As the next phase, the authors anticipate predicting the minimum and maximum temperature, relative humidity, and yield. The authors want to construct the final model by integrating all these parameters to choose acceptable crops. At last, this research might be advanced by combining these models with IoT devices.

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