Machine learning based Pedantic Analysis of Predictive Algorithms in Crop Yield Management

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Abstract— **Predictive analytics is a statistical technique used to forecast and investigate the development from past chronological data or to extract the information from data. With the help of rising technologies like predictive analytics in data mining, machine learning combining with Internet of Things [IoT], the major challenges in crop yield can be solved and pave way to earn profit. Machine learning means the process of making the system to learn from the previous experiences that help in prediction. In this paper, an conjectural evaluation on diverse prediction algorithms like support vector machines (SVM), recurrent neural networks (RNN), K nearest neighbour regression (KNN-R), Naïve Bayes, BayesNet, support vector regression (SVR) etc., is done and its performance are described on the basis of error rates and accuracy level in crop yield. BayesNet shows the higher accuracy of about 97.53% and RNN has less percentage error rates that dominate other algorithms in harvest prediction.**

Keywords— Crop yield; IoT; Machine Learning; Prediction algorithms

I. INTRODUCTION

Due to an augmented population and stipulate in food production, agricultural sector becomes more prevailing among all sectors as well as it plays a vital role in our India's economy. Fig.1. is the flowchart of crop yield management system and explains the steps of crop yield.

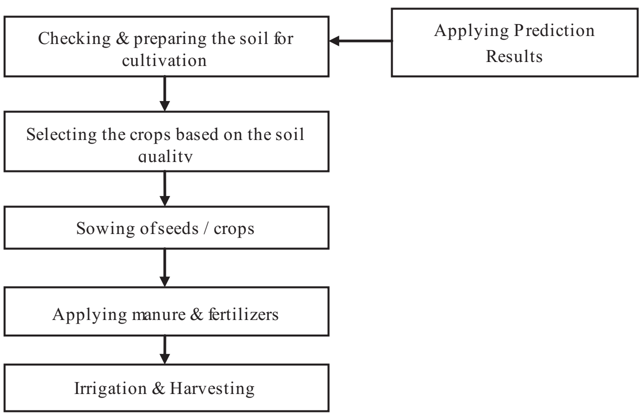

Fig. 1. Crop Yield System

Amongst all, decision making is the main predicament due to the paucity of water, soil eminence, climatic changes, and so on. To conquer this, farmers need the precise and judicious prediction about the water requirement for particular crop fostering, needed soil quality, quality and usage of fertilizers, seeds quality, and use of pesticides. Also, if cropping area management has been improved, then it increases the crop yield with respect to food production order. Technologies like Data Mining, Machine Learning, and Internet of Things in the agriculture field are incorporated to achieve the high crop yield. Data Mining is a technique which helps to extort the data from the assorted datasets and able to act upon the analysis part in that datasets by ruling out the recurrent patterns or association analysis, by cluster the data's according to its feature resemblance, or classifying the data based on the category, the data belongs to. Machine Learning is another emerging technology which trains the system based on the prior experience from the training datasets. Internet of Things is a budding technology which helps to distribute the data efficiently, to control the remote sensing devices like temperature sensors, moisture sensors, humidity sensors etc. In these data sets, machine learning algorithms or data mining algorithms can be implemented to get the best forecast results. The accuracy of various predictive algorithms can be calculated in terms of error rates such as Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error etc., Where, MAE [18] is the absolute mean values on all attributes for all prediction error.

It is calculated by $MAE = \frac{\sum_{i=1}^{n} abs(ti - \frac{\lambda}{\mathrm{pi}})}{n}$ (1)

MSE is the summation of all data points, whose difference is calculated between the predicted and actual target variables square value, is divided by n the number of data points.

$$MSE = \sum_{i=1}^{n} \frac{(W^T p(i) - t(i))\hat{}2}{n} \quad (2)$$

RMSE is the Mean Square Error's square value which means the target variables square.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (si - oi)^2} \quad (3)$$

There are abundant studies and researches have been conceded to progress the crop productivity based on these technologies.

II. LITERATURE WORK

In this paper, investigation has been conceded to scrutinize the accuracy and efficiency of the various prediction algorithms which is suitable for crop productivity and cropping area management.

A. *Accurate Prediction using Long Short Term Memory & RNN*

There are two modules projected [17]. One is to predict the reap of paddy and other is to foresee the stipulate of rice. Two algorithms are used to perform the prediction from machine learning. 1. RNN 2. LSTM. The RNN [16] is explained as a directed graph and establishes a correlation between each node in a chronological manner. In RNN, dynamic temporal behavior has been recognized with the help of various inputs that are independent of each other. This feature helps RNN to produce best prediction results. In RNN, each node sends the message to the next node as an output feedback. LSTM [17][31] is another module which predicts the rice demand. It has the capability to learn the long term dependency between the elements. Approximation algorithms like Genetic algorithms, Iterated local search can also produce best results for resource optimization and planning issues.

B. *Autoregressive Integrated Moving Average (ARIMA) model in crop yield*

Machine learning algorithms like Autoregressive Integrated Moving Average (ARIMA) model and KNN are used along with IoT and Image processing techniques [3]. By usage of this technique, the improvement in crop productivity and reduced the usage of chemical fertilizers has been shown. The input values like N, P, K, pH and temperature of the soil from these farm areas are unruffled. ARIMA uses the past values to predict the future time series value Y. It is a time series model which uses three parameters called p, d, and q parameters where p represents the differencing degree of integrated component, d is the parameter which represents the order of moving average in d times and q represents the number of slacks used in the model. Thus, KNN [11] [22] classifier classifies the inputted forecasted values and produces the output values against the nutrients provided.

C. *Automatic Phenology Based Algorithm for Rice Detection*

Automatic rule based method is anticipated [5] [25] by collecting the sentinel 2 data based on the three factors to perceive the rice crops from other crops. The factors are Near Infrared reflectance during the fostering time, Red band reflectance during the reap time and Normalized Difference Vegetation Index (NDVI) Values. The major challenges faced while using SVM are: 1. Number of classes, 2. Identify the precincts of the classes, and 3. Select the textural and polar metric features. In this exploration, ML are time consuming and expensive, whereas rule based reduces the necessity of ground data that covers the temporal shift during cultivation, detects and classify the rice crops efficiently has been concluded.

D. *Chi-square automatic interaction detection algorithm (CHAID) in Crop recommendation system*

The model for precision agriculture is anticipated [23] with the help of learners like random tree, CHAID [13], KNN [20] and Naive bayes with predictable high accuracy and efficiency. The dataset consists of parameters like depth, texture, pH, soil color, permeability, drainage, and water holding and erosion ability of soil. CHAID is used to calculate the similarity between the attributes. K-Nearest neighbor is used to store all the available cases and on the basis of similarity measure, it classifies the new cases. In KNN [11] [21], based on the nearest element, the set is classified. Nearest element is calculated using the Euclidean distance. Naive Bayes is meant as a technique used to construct the classifier models by assigning the class labels to instances. The prediction accuracy of this model is 88%. Naive bayes works well as a classifier model has given as a conclusion in this research.

E. *Intelligent Information Predictive Analytics and Iterative dichotometer3*

Intelligent information predictive analytics systemhas been established to determine the area based rank of beneficial crop [27]. The stagnant dataset has been analyzed in delve into by using supervised machine learning techniques. The main intention described is to afford an erudition agent, which helps in taking farm decisions more lucrative and proficient. This research provides a favorable crops list by using decision making algorithms called decision tree learning, KNN and Iterative dichotometer3 (ID3) [38] are called prediction algorithms that are used to analyze the different crops production yield. Decision tree algorithm is described as the classification of large data and extracting the dataset that has similar / same patterns. ID3 is used for dataset classification by analyzing the information gain with the help of attributes. Entropy means the number of uncertain data of the dataset.

$$\text{Entropy(S)} = -\sum \boldsymbol{p(X) * log\ 2\ (p(X)).}\ ) \qquad (4)$$

Here S indicates the entropy calculated. In KNN regression [29]. Euclidean distance can be calculated between the average rainfall and temperature value that can be obtained from the learned and test data.

F. *Long Term Time Series (LTTS) and Support Vector Regression (SVR)*

A novel approach [14] is proposed for sugarcane yield called Long Term Time series (LTTS) [31][32] Normalized Difference Vegetation Index (NDVI) [9][12] and Support Vector Machine Regression [29]. LTTS is called as time series which needs multistep predictions to predict the future values based on the past time series values and current time series values [36]. The proposed model is categorized into three stages. Stage 1 describes the predicted weather and soil attributes of Sugarcane Cultivation Life Cycle (SCLC) duration. Stage 2 describes the predicted NDVI by taking weather and soil attributes as an inputs. Stage 3 predicts the sugarcane crop yield by taking the predicted NDVI value as an input. This can be done with the help of SVR algorithm. SVR machine learning algorithm produces high accuracy in crop yielding of about 83.49% and also produces high accuracy of 89.97% for prediction of NDVI is concluded.

G. SVM and Bayesian Network Algorithm

Data mining algorithms and machine learning techniques like K-Means clustering, KNN, SVM, and Bayesian Network Algorithm [34] is used to produce high accuracy in a given dataset. A support vector [7][8][30] is defined as the coordinates of a particular class or used to develop functions of a labeled training data. Another method called selective attribute classification can be used to construct the classifiers. It is used as data mining algorithm called K Nearest algorithm. It is otherwise called as supervised learning and lazy algorithm. The major disadvantage is that for each sample, nearest neighbor is to be determined.. Also it requires lot of time for calculating the distance between test data and training data. In crop prediction, Artificial Neural Networks [6] and Neural Networks classification approach works well and shows better improvement in the performance of classifiers has been drawn as a conclusion.

H. IOT based Machine Learning Analytics

IOT model for farming module has been designed and developed [34] [35] by using the cloud based machine learning analytics to predict the crop cultivation condition based on the past experience. Tensor flow is used to train the logistic regression based model by taking the dataset as an input and produces the optimal condition for the particular crop [10]. The advantage of this research is cost efficiency and reduces the labors required for the farm. But the main disadvantage of this paper is lack of access to the real time data and lack of equipment control over the farm when the farmer is out of station/ out of town.

I. Bayesian networks evaluation using WEKA

The dataset that has the parameters like precipitation, minimum temperature, average temperature, maximum temperature, reference crop evapotranspiration, area, production and yield from 27 districts of Maharashtra has been analyzed using WEKA tool [7]. BayesNet [18] and Naïve Bayes [2] are used as classifiers to classify and predict the yield of rice crop in the Maharashtra region. The performance of classifiers in terms of sensitivity, specificity and accuracy is evaluated where, sensitivity is the percentage of True positive and negative instances, specificity is the percentage of false positive and negative instances and accuracy describes the overall success rate of the classifier. The BayesNet algorithm works better than the Naive Bayes which produces the maximum accuracy as 97.53%, maximum sensitivity as 96.31% and specificity as 98.16%. It shows the error rates named Mean Absolute error as 0.0425, RMSE as 0.1449, RAE as 9.56% and RRSE as 30.71%. Based on the F1score and MCC, it produces 0.96 and 0.94 as maximum value. While using SVM in the same dataset, it produces an accuracy as 78.76 %, sensitivity as 68.17%, specificity as 83.97%, F1 score as 0.69, MCC as 0.54, MAE as 0.23, RMSE as 0.39, RAE as 67.38% and RRSE as 82.51%.

J. IoT Monitoring System with Predictive Analysis

Based on the cloud based IoT platform infrastructure [1], a sensing network has been developed to collect the crops data from the farm area. This infrastructure has three layers, namely first layer called Perception layer which includes the hardware parts from which the data has been collected and later it has been analyzed by gateway layer. Second layer called gateway layer which acts as a bridge between perception and application layer. This can be formed using raspberry pi 3 microcontroller that provides power for processing and storage for data analysis. Third layer is named as an application layer. In application layer, with the help of data visualization [33], a technique used to code the different entities of data by using its visual features helps the end user to connect with the sensed data.

K. Supervised Kohonen Networks & XY-Fused Networks in wheat crop yield

According to the online multilayer data of soil and characteristics of satellite imagery [19], the prediction can be done for wheat crop yield from the variations in field. To handle the existing information from different soil and crops, supervised Self Organizing Models (SOMs) are used. CP-ANNs [6] can have the capability to combine the features of supervised and unsupervised learning techniques. It has two layers, namely input or Kohonen layer contains vector representation structure input values and consists of nx x ny neurons. The output layers contains p- component vector of 0's and 1's as an output values. XY- Fused network [15] uses Euclidean distance to select the winning neuron. SKN [28] are otherwise called as supervised neural networks that can be used to determine the output value from SOMs which finds the classification model. Finally, it is concluded that SKN provide 91.3% accuracy for both cross and independent validation.

L. Random forest and Naïve Bayes for crop recommendation system

Tested soil from polytest laboratory has been given as an input to the crop recommendation system [26] and performs ensemble with the help of learning technique such SVM, Random forest, ANN, and Naïve Bayes. Ensemble [4][37] is otherwise known as the Model Combiners of data mining model that merges the two or more models strengths to achieve the high accuracy prediction results. Ensemble can be performed if one or few attributes produces an error, other members has corrected the errors in high probability. Also, a model can be created by the learners itself. In ANN [24] Multilayer perceptron is considered as feed forward neural network that has several layers laid between input and out end layer. Random Forest square is used to measure the classification, regression and various tasks performed by ensemble learning techniques.

III. OBSERVATIONS

Through this research, various prediction algorithms are studied along with its performance measurement parameters like accuracy levels, MAE rate, RAE, RRSE rate, RMSE rate, sensitivity, specificity, MCC, GDD threshold values and NDVI accuracy levels are studied. Some of the evaluation results are given below.

In crop yield management, LSTM and RNN [17] comparison results are shown below in Fig. 2.

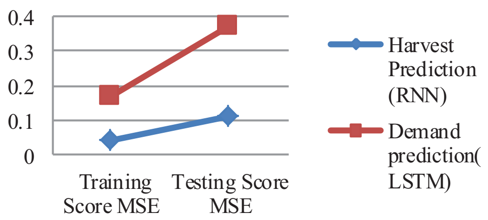

Fig. 2. Comparison results of LSTM and RNN

The reflectance mean value in red and Near IR bands, differentiation of rice crops are more and it is shown below along with other crops Fig.3. It shows that, during cultivation time, Near IR reflectance occurs whereas, during harvest time, red reflectance occurs. The accuracy of SVM and ML are given as 81% and 57%.

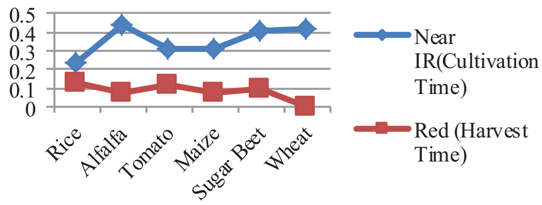

Fig. 3. Mean Reflectance values of various crops obtained from NDVI

The error rate values of various crops obtained using ID3, DTL and KNN of Tangail region, Jessore, and Barishal region are shown in the below fig 4 & 5.

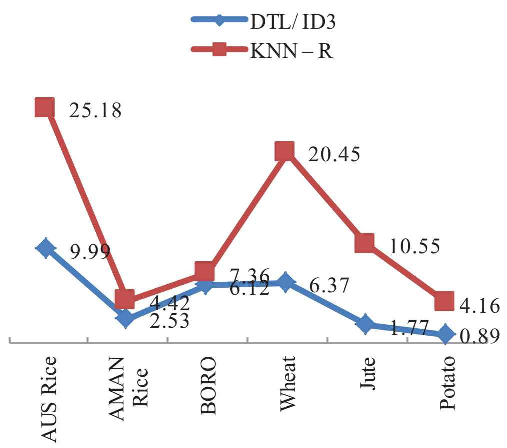

Fig. 4. Comparative results of DTL/ID3 & KNN-R in Tangial Regions

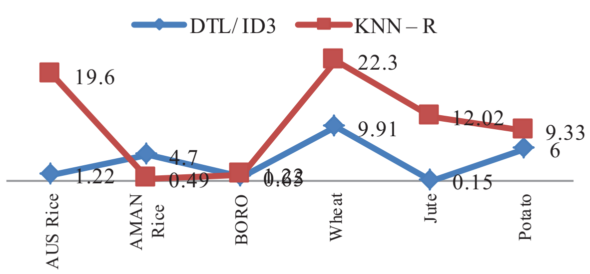

Fig. 5. Comparative results of DTL/ID3 & KNN-R of Barishal region

The accuracy values of predictive algorithms like SVR, GBR, Kernel Ridge RBF and Lasso regression are shown in the below table I:

TABLE I. ACCURACY OF VARIOUS MACHINE LEARNING ALGORITHMS

Parameters Algorithm	NDVI Accuracy %	Median	Crop Yield	Median
SVR	89.97	87.98	83.49	80.41
	82.02		74.53	
GPR	71.23	64.81	81.71	78.39
	46.86		74.29	
Kernel Ridge RBF	80.32	77.05	21.66	19.68
	66.86		17.03	
Lasso Regression	59.94	58.36	27.03	24.41
	50.31		21.77	

The overall accuracy in cross validation for three algorithms is shown below for high wheat yield in fig.6

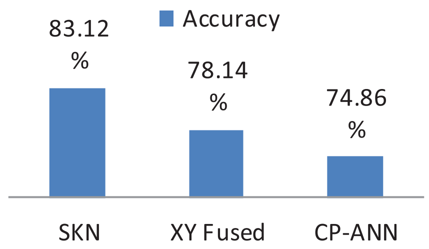

Fig. 6. SKN, XY Fused & CP-ANN Accuracy results by Cross validation

For high wheat yield, the overall accuracy in independent validation for three algorithms is shown in fig.7.

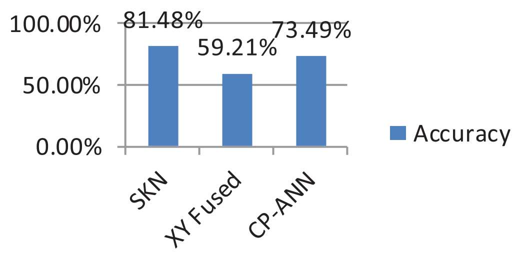

Fig. 7. SKN, XY Fused & CP-ANN Accuracy results by independent validation

Most of the researchers have preferred an optimized algorithm through which the farmers can increase the crop productivity and increased the profitability.

IV. PERFORMANCE EVALUATION & DISCUSSION

Through this analysis, so many predictive algorithms are intentional with its accuracy values and mean squared error rates. Overall performance evaluation results are given below in table III & IV.

TABLE II. PERFORMANCE MEASURE BASED ON ERROR RATES

Algorithms	Rates
RNN	0.08
LSTM	0.25
SVM	0.39
Naïve Bayes	0.29
DTL/ID3	4.8
KNN-R	10.26
BayesNet	0.14

TABLE III. PERFORMANCE MEASURE BASED ON ACCURACY LEVELS

Algorithms	Accuracy %
Bayes Net	97.53
Naïve Bayes	84.69
SVR	84.20
SVM	78.76
RNN	78
LSTM	74
GPR	71.6
KR-RBF	48.37

V. CONCLUSION

To conclude, agriculture remains as a backbone for humans living across the globe and it plays a vital role in the economical development of the country. In this research paper, various algorithms are calculated and their performances are evaluated. The entire algorithm operates well with different factors but when considering error rates as performance measure, recurrent neural network (RNN) works well when compared to other algorithms. When considering accuracy as performance measure, BayesNet performs very well for rice crop and produces an accuracy of 97.53%. Lasso Regression produces a minimum accuracy of 41.38%. When an optimized genetic or prediction algorithms is used, it will produce better results when combined with IoT infrastructure in the farm. This can make a notable increase in the crop productivity and economical development.

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