A Survey on Crop Yield Prediction Using Machine Learning

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Abstract

Since ancient times, agriculture is one of the most critical occupations in India. India is considered the world's second-largest in outputs. Agriculture is the most critical sector and plays a vital role in the Indian economy, which contributes around 17% of total GDP and 60% of the entire workforce, according to the assessment of 2018. Different seasonal, economic and biological patterns affect crop production, but sudden changes in these patterns lead to a significant loss to farmers. Crop yield prediction is a fundamental issue in agriculture. By analysing various relevant factors, like location, crop type, PH value of soil, type of soil, percentage of nutrients like Phosphorous (P), Nitrogen(N), Potassium(K), humidity, temperature and amount of rainfall, we can forecast crop yield using Machine Learning. Different approaches have been used to produce models and interpret final effects, such as Regression, K-means, Decision Trees, Random Forests, Support Vector Machines, Bayesian Networks, Artificial Neural Networks, etc. Such approaches help analyse the environment, soil and water processes heavily involved in crop growth and precision farming. An overview of some of the latest supervised and unsupervised machine learning models linked to crop yield in literature is highlighted in this survey paper.

Keywords: - *Crop yield Prediction, Machine Learning, Agriculture, Classification, Regression*

INTRODUCTION

According to projecting data from United Nations, The world's population will climb up to9.7 billion by 2050 [1], [3], which interprets that the world population will grow by 30% in the next 30 years. To feed all these populations, a dynamically boost in agricultural productivity is vital to fight a potential food gap [2], [3]. For Every providence or country, consistent crop yield assessment has become a crucial and strategic process to forecast the total volume of crop products which can help decide what could be imported/exported in case of shortfall or surplus, respectively [8]. Conventionally, regional crop production information of many countries have been computed using ground-based observations and the production reports; however, data assembling based on ground-based field visits is expensive, time-consuming and mostly incompetent while raising concern about the consistency of the process that could lead to poor crop yield assessment [4]. For the decision-making process of import and export of goods mentioned above, these datasets are mostly collected too late. [5]. Hence, in recent decades, continuous monitoring of crop yield & status is the most debatable topic for industries [9]. Crop yield prediction is tremendously tricky due to various multifaceted aspects. Climatic condition, soil quality, landscapes, pest infestations, water quality and handiness, genotype, scheduling of harvest activity & so on are the most critical factors behind superior crop yield [12]

Artificial intelligence is an enormous field containing vast regions like probability, logical reasoning and computing. Machine Learning is a division of the broader field of artificial intelligence and an immediate successor of statistical models appropriating valuable information from a heap of data [7]. In machine learning, computers are instructed without writing programming. These processes overcome agricultural frameworks based on linear or non-linear with incredible forecasting ability. All techniques are obtained from the learning process in Machine learning agricultural frameworks. These processes require training to perform a particular task. Once the training method is completed, the model makes presumptions to check the information [12]. Machine learning is categorised into four divisions. They are as follows:

1. Supervised learning
2. Semi-Supervised learning
3. Unsupervised learning and
4. Reinforcement learning

A supervised machine learning algorithm works with the unknown dependent/target variable predicted from a given set of known predictors based on label data. Similarly, unsupervised machine learning algorithms can be performed on the target variable predicted with a set of a similar group of data items called clustering based on unlabeled data. A semi-supervised machine learning algorithm falls between Supervised and Unsupervised collection of data items. In the reinforcement learning algorithm, agents interact with the environment by taking suitable action to make the most of the reward in a particular situation [6].

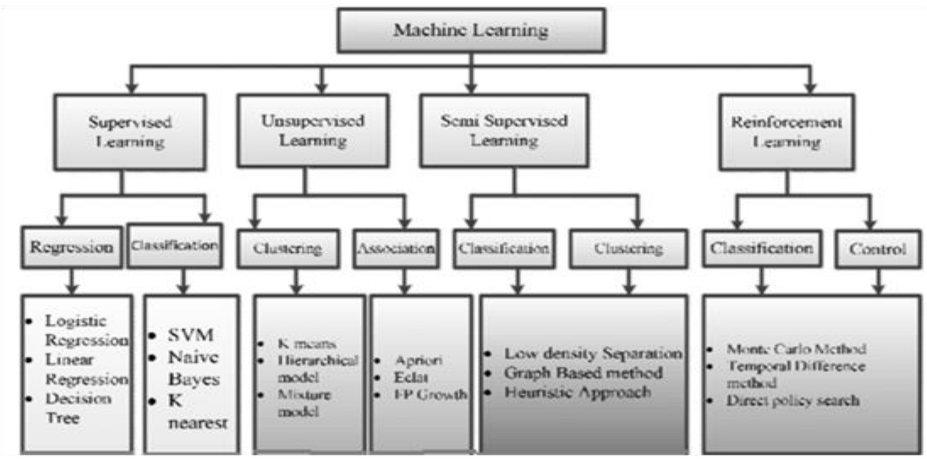

Figure 1 Types of Machine Learning

The Second sections brief the related work of crop yield prediction. The third section details the Factors influencing crop yield. The fourth section describes the methodology for implementing the machine learning algorithms to forecast crop yield. The fifth section discusses the results and various evaluation metrics used for result analysis. The sixth section concludes the survey and discusses future scope.

RELATED WORK

P.S. Maya Gopal et al. proposed a data-driven hybrid model to predict paddy yield accuracy when Multiple Linear Regression(MLR) intercept and coefficient were applied to Feedforward back-propagation Artificial Neural Network(ANN by using area, number of open wells, number of tanks, canals length and maximum temperature during the season features. [8]

Hossein Aghighi et al. have enlightened yield prediction of silage maise based on time series of NDVI dataset derived from Landsat 8 OLI by boosted regression tree (BRT), random forest regression(RFR), support vector regression, and Gaussian process regression (GPR) approaches and compared their performance with some future conventional regression methods[9].

Petteri Nevavuori et al. used CNN with 6 conventional layers to demonstrate outstanding performance in the image classification task and construct a model based on RGB and NDVI data acquired from UAVs for barley and wheat yield prediction. This research interprets RGB data with CNN architecture performed better than the NDVI data with CNN architecture.[10]

Rai A. Schwalbert et al. proposed in-season ("near real-time") soybean yield forecasts in southern Brazil using three different algorithms Linear regression, random forest and Long-Short Term Memory (LSTM), Neural Networks, satellite imagery and weather data and LSTM neural network give superior performance relative to other algorithms.[11]

Dhivya Elavarasan et al. proposed a Recurrent Neural Network deep learning algorithm over the Q-Learning reinforcement learning algorithm to forecast the Paddy yield in Vellore by using different Soil, Weather, Ground Water Property and achieved 93.7% accuracy and preserved original data distribution.[12]

Durai Raj Vincent et al. have proposed reinforce extreme gradient boosting on paddy crop which displays improved execution over traditional machine learning algorithms like an artificial neural network, Deep Q- Network, gradient boosting, random forest and decision tree based on Soil, Weather and Groundwater property with an accuracy of 94.15 %.[13]

Amir Haghverdi et al. used the ANN approach from the phonology of crop indices to estimate cotton lint. By using remote sensing technology, the study is performed on a 73-ha irrigated field of western Tennessee. 61200 models relating to individual crop indices and eight input predictors were generated using the ANN model to field estimates of cotton yield to be predicted [14].

Abrougui et al. proposed the yield prediction of potato crops using the soil properties and the ANN tillage method. It is evaluated by including soil microbial (MB), soil resistance to penetration, soil organic matter (OM). To estimate potato yield, predictive capacities of MLR and ANN methods are assessed and found that potato yield affected by soil property and tillage system. The ANN model showed great potential over other methods [15].

Byakatonda et al. used the ANN model to predict maise and sorghum crop yield using the spearman's rank correlation to consider the climatic indices and precipitation period. Yield predictions are made using ANN models to facilitate agriculture planning. Maise yields are more associated with climatic indices than sorghum yields. ENSO accounts for variations of 85% in maise and 78% in sorghum yield. [16]

Khosla E et al. proposed ANN, SVM regression model for yield prediction of major Kharif crops based on rainfall data of Visakhapatnam distinct. Crops included in this study are Bajra, Rice, Ragi and Maize. In this study, they first predict monsoon rainfall by using a modular artificial neural network and then the expected amount of major Kharif crop that can be yielded by using the rainfall data and area given to that particular crop by using support vector regression [17].

Table 1-Comparison of Different algorithms used for crop yield Prediction

Paper Name	Publication Year	Algorithm/Methods	Crop Name and study Area	Data	Validation Technique/result
A novel approach for efficient crop yield prediction[8]	ELSEVIER-2019	ANN,MLR	Paddy Crop in Tamil Nadu Area	Agriculture Production Data- planting area, irrigation area, fertiliser usage and irrigation details, Whether Data- rainfall, maximum and minimum temperatures and solar radiation.	RMSE-0.51 MAE-0.041 R-0.99
Machine Learning Regression Techniques for the Silage Maize Yield Prediction Using Time-Series Images of Landsat 8 OLI [9]	IEEE-2018	boosted regression tree, support vector regression, Gaussian process regression, random forest regression	Silage Maise Crop in Ardabil, Iran.	NDVI time-series dataset of different Fields	RMSE-6.07 MAE-4.85
Crop yield prediction with deep convolutional neural networks[10]	ELSEVIER-2019	Convolutional neural network	Wheat, Barley Vicinity the city of Pori	Image Data based on RGB and NDVI data acquired by UVAs.	E-MAPE-8.8% L-MAPE-12.6%
Satellite-based soybean yield forecast: Integrating machine learning and weather data for	ELSEVIER-2019	Long-Short Term Memory	Soybean Southern Brazil	satellite imagery and weather data	MAE-0.24% RMSE-0.32% MSE-0.10%

improving crop yield prediction in southern Brazil[11]					
Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian Applications[12]	IEEE-2020	Deep Q- Network	Paddy Tamil Nadu	Soil, Weather, Ground Water Property	R2-0.87 MAE-0.13 MSE-0.03 RMSE-0.17 MedAE-0.11 MSLE-0.002 Accuracy-93.7%
Reinforced XGBoost machine learning model for sustainable, intelligent agrarian[13] Applications[24]	Journal of Intelligent & Fuzzy Systems-2020	XGBoost	Paddy Vellore, Tamil Nadu	Soil, Weather, Ground Water Property	R2-0.88 MAE-0.12 MSE-0.02 RMSE-0.14 Accuracy-94.15%
Prediction of cotton lint yield from phenology of crop indices using artificial neural networks[14]	ELSEVIER-2018	ANN	Cotton West Tennessee	Used eight input predicators Red, near infra-red, the simple ratio, NDVI, green NDVI, greenness, wetness, and soil brightness	In 2013-r = 0.68 MAE = 11% In 2014- r = 0.86 MAE = 8%
Prediction of organic potato yield using tillage systems and soil properties by an artificial neural network (ANN) and multiple linear regressions (MLR)[15]	ELSEVIER-2019	MLR ANN	Potato	Soil Properties	R2= 0.97 RMSE=0.077
Influence of climate variability and length of the rainy season on crop yields in semiarid Botswana[16]	ELSEVIER-2018	ANN	Maise Sorghum	climatic indices	ENSO accounts for variations of 85% in maise and 78% in sorghum yield.
Crop yield prediction using aggregated rainfall-based modular artificial neural networks and support vector regression[17]	Springer-2019	ANN SVM regression	Bajra Rice Ragi Maise Visakhapatnam	Rainfall	RMSE for Bajra-10,749 t Rice-10,749 t Ragi-1731 t Maize-1696 t

FACTORS INFLUENCING CROP YIELD

There are a variety of factors related to crop yield and the uncertainties involved with cultivation. Soil fertility, ease of water, and pests or diseases are the most significant factors that impact crop yield. These factors can do an enormous hazard to farmers when they are overseen precisely. Furthermore, to enlarge the crop yield and to diminish the risk, it crucial to see exactly what impacts crop yield in-depth.

Soil fertility

The soil is full of essential nutritional supplements for crops, like nitrogen, phosphorus, potassium, calcium, magnesium, sulfur, iron, manganese, and so on, essential for suitable crop development [18]. They are equally important to the crops, even though they are required in limited varying quantities. These distinctions have urged the gathering of these fundamental elements at the micro and macro level [19]. The accountability of nutrients in plants is complex, used in processes like root, shoot, leaf and fruit development, the formation of proteins, hormones and chlorophyll, photosynthesis and so forth. The soil is a significant wellspring of these nutrients to crops, and soil fitness can consequently affect crop generation [20]. The lack of these supplements can reduce the crop yield by perversely influencing the related growth factor.

Water availability

It can be un-debatable that the accessibility of water directly affects crop yield and productivity. It can hence change largely because of the exceptionally diverse nature of precipitation in terms of both quantity and time span [21]. A minimal amount of rainfall can make crops shrink and die, while on the other hand, extreme rainfall will likewise have an unfavourable effect on crop development. When crops are over flooded, water, fertiliser, labour, and energy are overwhelmed, and crop development can moderate [22].

Climate

Amongst the most ignored factors that impact crop development is climate [23]. Climatic conditions extend out past merely wet and dry. While yearly rainfall is a crucial part of the atmosphere, several different viewpoints are considered, like temperature, humidity, wind, expanded predominance of pests amid certain atmospheric conditions and weather patterns [24]. Inconsistent patterns or frequent climate changes imply a massive risk to crops, as they can severely damage them. It might be favourable conditions for the growth of specific pests and weeds. After the development of pests or weeds, they cause damage to goods.

Pests and crop disease

Pest and crop disease are among the most substantial factors that impact crop yield [25]. They are coming with enormous species which damage the crop in various ways. There are some specific bugs like plant parasites that can similarly damage in unusual ways [26]. For example, some Pests attacks roots of plants reduce capacity to absorb water and the nutrient. Thus, plants become more susceptible to various diseases.

MACHINE LEARNING ALGORITHMS FOR CROP YIELD PREDICTION

Machine learning, an application of artificial intelligence (AI), provides the device with the ability to learn and improve information without being programmed directly. Machine learning differs from AI and deep learning. The advantage of machine learning is to train the model depending on the data available to predict the approach with higher efficiency. Machine learning can be divided into two main segments: Supervised and Unsupervised. There are many different algorithms.

Supervised machine learning algorithms

In the Supervised learning method, we use feedback from human resources and tanning information to analyse the relationship between input and output data.

For example, a specialist can use marketing outlay and weather outlook as input information to identify the sales of cans[31]. One can use supervised learning if the output info is known, and the algorithm will identify new data. Supervised learning is different categories into[31]:

- Classification
- Regression

Classification

A classification problem is when the output variable is a category, such as "red" or "blue" or "disease" and "no disease". A classification model attempts to draw some conclusions from observed values [27]. Given one or more inputs, a classification model will predict the value of one or more outcomes [27].

Regression

A regression problem is used in such a case when the output variable is a natural or continuous value, such as "salary" or "weight". Many different models can be used for regression. Among that, the simplest method is linear regression. It tries to fit data with the best hyper-plane, which goes through the points [27].

Table 2- Supervised Machine Learning Algorithm [31]

Algorithm Name	Description	Type
Linear regression	It is used to show the relationship between predictor variables and crop yield as a response variable.	Regression
Logistic regression	Expansion of linear regression that is utilised for characterisation assignments. The yield variable is paired (e.g., just dark or white) as opposed to consistent (e.g., an endless rundown of potential hues)	Classification
Decision tree	Using a decision tree, we can predict crop yield's influence by using a long-term dataset. The objective of the decision tree is to train a model to forecast a class or a target variable through decision rules implied by the training data. A tree representation described from a root node to a leaf node is used to solve the problem. Based on the type of the variables, which is discrete or continuous, a classification or regression tree is constructed. A regression-based decision tree is built to predict the crop yield of a concerned area based on climatic factors.	Regression Classification
Naive Bayes	Navie Bayes method is used for classification purposes. The Bayesian technique is a characterisation strategy that utilises the Bayesian hypothesis. The hypothesis refreshes the earlier information of an occasion with the free likelihood of each element that can influence the occasion[31].	Regression Classification
Support vector machine	SVM is used to extract the information regarding crop growth and also used for the grouping task. SVM finds out a hyperplane that separates different classes. It is best utilised with a non-linear solver.	Regression (not very common) Classification

Random forest	In general, Random Forest produces simple decision trees and uses the 'majority vote' technique to pick which mark to return. The one with the most votes will be the last expectation for the arrangement task, while the previous expectation for the relapse task is the normal estimate of the significant number of trees.	Regression Classification
Gradient-boosting trees	Classification or regression strategy uses many models to think of an option but tests them based on their accuracy in predicting the outcome.	Regression Classification
AdaBoost	A gradient-boosting tree is a classification/regression technique for the cutting edge. It reflects on the confusion raised by the former trees and tries to fix it.	Regression Classification

Unsupervised machine learning algorithms

In unsupervised learning, a calculation investigates input information without giving an unequivocal yield variable (e.g., investigates client statistic information to recognise designs) [31]. If you do not know how to order the details, you can use it, and you need the calculation to discover designs and characterise the data for you.

Table 3 - Unsupervised machine learning algorithm [31]

Algorithm Name	Description	Type
K-means clustering	Places information into specific gatherings (k) that each contains information with comparable attributes (as controlled by the model, not progress of time by people)	Clustering
Gaussian mixture model	Speculation of k-means clustering that gives greater adaptability in the size and state of gatherings (groups)	Clustering
Hierarchical clustering	To frame a grouping system, a portion bunches along a multiple levelled tree. Can be used for Cluster Customer Unwaveringness Card	Clustering
Recommender system	Support to identify the essential data for making a recommendation.	Clustering
PCA/T-SNE	The dimensionality of the data is typically reduced. The equations limit the number of highlights with the largest variations to 3 or 4 vectors.	Clustering

APPROACHES FOR OBTAINING RESULTS AND METRICS OF EVALUATION

Assessment of the models depending on the metrics and dataset determines the competence of the model. The machine learning models built to estimate crop yield under various climatic conditions are evaluated to determine their performance efficiencies. The different performance metrics used to assess in the study are as follows:

- Root Mean Square Error (RMSE)
- Relative Root Mean Square Error (RRMSE)
- Mean Absolute Error (MAE)
- Determination Coefficient (R2)

Root mean square error

The computations of the standard deviation of the prediction errors, i.e., the residuals, refer to the deviation of the data points from the regression line. RMSE is the computation of the spread of the residuals. It determines the concentration of the data around the best fit line. Root mean square can be calculated as follows:

- Finding the square of the residuals.
- Calculate the average of the residuals.
- Compute the square root of the result. [28]

$$\mathrm{RMSE} = \sum_{i=0}^{N} \sqrt{\frac{y_i - y_i'}{N}} \qquad (1)$$

Relative root mean square error

The relative root means the square error is the normalised value of the RMSE. It is defined by dividing the RMSE value by observed mean data. The relative measures are symmetrical and are resistive to the outliers. It also helps to establish weak bias estimates [29].

$$\mathrm{RRMS} = \frac{\sum_{I=1}^{N} \sqrt{\frac{(y_i - y_i')^2}{N}}}{\frac{\sum_{i=1}^{N} x_i}{N}} \qquad (2)$$

Mean absolute error

In a set of predictions, MAE measures the mean of the error magnitudes, ignoring the direction. This can be defined as the average of the absolute difference between the predicted and the actual value in different terms. Here all the individual differences are weighted the same[30].

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - y_i'| \qquad (3)$$

Determination coefficient

It is used to analyse the difference in one variable in terms of the second variable difference. In other words, it reveals the percentage change in variable y in terms of variable x. It is the square of the correlation coefficient measure [30]. It is calculated as follows:

$$R_2 = \left(\frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}\right)^2 \qquad (4)$$

CONCLUSION

Agricultural tests would help the agricultural bodies to support farmers in making meaningful and profitable decisions. In this paper, we conducted a survey of machine learning techniques for crop yield prediction and identified various algorithms such as ANN, MLR, Boosted Regression Tree, SVM, and Random Forest. ANN is the most widely used algorithm among these algorithms, and temperature, rainfall, and soil type are the most commonly used features. This paper incorporates the work of numerous writers in a single spot so that it is helpful for specialists to obtain data on the current circumstances of the methods and their substantive application to the agricultural field. Different machine learning models find a near-optimal minimum of error, and it will increase accuracy for yield prediction and find prediction accuracy standard performance metrics are used.

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