

Automated Crop Yield Prediction System Using Machine Learning Algorithm

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ABSTRACT

Agriculture is one of the most important sources of food and one of the most important social problems. Due to expanding populations, food scarcity or shortages are presently a problem in many nations. Crop production prediction is challenging due to several complex factors. Crop production is often influenced by a range of variables, such as timing of harvest, weather, water availability, water quality, genotype, insect infestations, soil quality, terrain, and others. Based on prior performance and trustworthy historical data, farmers used to anticipate crop production and then make significant cultivation decisions in line with the projections. Using a range of features, machine learning (ML), a branch of artificial intelligence (AI) that focuses on learning, is a practical technique that can estimate yields more precisely. The major goals of this research are to estimate crop yield production using a machine learning algorithm and to provide farmers with an easy-to-use user interface.

Keywords: Crop; yield; prediction; machine learning; random forest; user interface.

1. INTRODUCTION

As one of the major sources of food, agriculture is one of the most serious societal issues. Numerous countries currently suffer from food shortages or scarcity as a result of growing populations [1]. Combined effect of growing population, erratic weather patterns, soil erosion, and a changing climate call for

strategies to guarantee timely and consistent agricultural development and output. Additionally, it must help increase the sustainability of agricultural food production [2]. These needs suggest that assessing land, protecting crops, and predicting agricultural yields are more crucial to the global food production [3]. The nation's policymakers must thus rely

on an accurate crop production projection in order to acquire simple import and export evaluation for increasing nation's food security. Whereas, predicting crop yield is difficult because of many complicated aspects. In general, a variety of factors influence crop production, including harvest scheduling, meteorological conditions, water availability, water quality, genotype, pest infestations, soil quality, terrain and others [4,5,6].

Processes and methods for predicting crop yields are inherently nonlinear and time-specific [7]. These techniques' inclusion of a wide variety of interconnected parameters which were influenced and specified by non-arbitration and external features [8], [9], makes them even more complicated. Farmers used to estimate crop yield based on their past experiences and reliable historical data and then make important cultivation decisions in accordance with the predictions.

However, in recent years, the development of newer technologies, such as machine learning (ML) based crop model simulation predicts yield accurately, coupled with ability to evaluate the vast quantity of data by higher performance computers [10-13]. Currently, several studies show that using machine learning algorithms has a larger potential than using conventional statistics [4], [14], [15].

Machine learning (ML), the subset of Artificial Intelligence (AI) which focus on learning, is a useful method that can estimate yields more accurately utilizing a variety of characteristics. ML extracts information from datasets by finding correlation and patterns. The models must be trained using dataset which depicts outcomes based on prior knowledge.

Multiple characteristics are used to build the predictive model, and as a result, using historical data, model parameters were determined during training stage. Test phase uses the subset of train phase historical data for performance assessment. Depending on the study challenge and research objectives, ML model will be either predictive or descriptive. Predictive models are being used to predict an outcome, whereas descriptive models were used to learn from data gathered also explain what has occurred. During an attempt to create higher performance prediction model, ML research face variety of difficulties. To tackle the issue at hand, it is essential to choose the appropriate algorithms, and both algorithms and the supporting platform will be able to handle the volume of information. We conducted the comprehensive literature study to gain an overview of the work have done on crop yield prediction using ML.

The main objectives of this research works are:

- a) Predict crop yield using machine learning algorithm.
- b) To offer a user interface that is simple to use.

2. LITERATURE SURVEY

Under [16] precision agriculture, changes in the field are identified and dealt with utilizing various strategies using geographic information system, distant sensors and technologies (PA). In an agricultural field, disease, pests prevalence, irrigation techniques, crop stress and other factors may be to blame for crop growth variability. Authors used Ensemble Learning.

[17] presents a comprehensive survey on application of ML in agricultural production systems. ML have evolved to provide newer chances for data intensive processing, analyze, measure, in agriculture operational sector together with digitalization, methodologies, approaches, and advanced computing. Authors used support vector machines to implement (SVM).

The agricultural yield prediction system employed in [18][30] uses machine learning. Technology This study's objective is to forecast agricultural production use Random Forest (RF) algorithm and pre historic data. Models were built using actual data from Tamil Nadu, they are tested with various samples. RF is used for precisely estimate agriculture productivity[32][31].

In place of “Multiple linear regression” and RF models, authors in [19]presented ELM AI model for predicting coffee production for small farm. Various ML models are compared with ELM model. The author asserted that when it comes to extracting features, ELM model were more effective compared to MLR and RF models. To forecast the agriculture production, supervised ML techniques like SVM, Decision Tree, RF, Polynomial Regression can be used[34][33]

To map soil characteristics and corn production at the local level, authors [20] developed a technique according to remote sensed data and ML methods like Cubist, Gradient boosting model, SVM, Neural Network, Random forest. The root mean square and model's accuracy are used to evaluate the remotely sensed data[35].

In order to generate crops over a certain time period, authors. [21] suggested an ensemble model combining several

classification techniques, including AdaNaive, AdaSVM, SVM, Naive Bayes. The suggested model, which was tested for accuracy, classification error, and AdaNaive conclusion, produces the best results for the rice crop, with accuracy of 96.52.

For regional and global crop yields of crops including potatoes, maize, and wheat as well as environmental factors like soil, climate, photoperiod, fertilization data, and water, authors [22] employed the random forest algorithm. The outcomes were compared with multiple linear regressions and assessed using actual vs. estimated plots, root mean square, index of agreement, Nash-Sutcliffe model efficiency. In the United States, the data is taken into consideration from several sources. Results indicated that Random Forest is a very accurate, precise, user-friendly, and data analysis-friendly technique for crop production prediction[36].

By using several categorization techniques and contrasting various factors, authors [23] came to the conclusion that their study aids to enhance the success of agriculture production rate, comparing different machine learning techniques to forecast agricultural production. Regularized greedy forests, KNN, SVM, ANN, decision tree, RF, gradient-boosted decision tree and developed “CSM technique (Crop Selection Method)”, that predicts crops sequence can be taken into consideration to plan in upcoming season, and algorithms were included to analyze flexibility. As a result, the accuracy and performance of the system vary depending on the parameters, the author found[37].

Researchers in [24] studied several data mining methods used to estimate

agricultural productivity and arrived to the opinion as data mining methods may be used to address the issue. A survey on use of data mining in agricultural industry generally, focusing on decision-making, was published by the authors in [25]. Researchers drew the conclusion, more research is necessary to verify the potential applications of data mining in complex agriculture statistics.

Various ML techniques and the application in plant biology were discussed by the authors in [26]. The difficulties and methods which were faced in image processing and ML in the agricultural sector, particularly in identification of disease, were discussed by the authors in [27]. The maturity of fruits was evaluated by the authors of [28][29] in order to determine good time for harvesting and forecast production. Survey on the use of ML in agriculture were released by the authors of [44]. The analysis was done utilizing papers which dealt with soil management, water management, crop management, animal management[43].

A literature review of ML models for agriculture production prediction based on meteorological factors were conducted by the authors of [45]. The article suggests using a broad lens to identify additional factors that affect crop productivity. Review research on nitrogen status estimated using ML was carried out by the authors in [46]. The report comes to the conclusion that the agriculture industry would benefit from fast advancements in ML and sensing technology[42].

A reliable crop prediction has emerged via the use of many strategies and procedures[40]. Numerous case studies are included, and it discusses the various approaches used for crop prediction in

detail. The majority of the concepts discuss ways to increase crop yields utilizing sensors, big data, SVM, all these were useful in predicting the crop[41].

For accurate crop yield prediction, RF Classifier is used in our research work[38]. The RF Algorithm carries out the number of operations that increase the accuracy of training and testing speed. The random forest classifier separates each distinct decision tree into the class prediction, and classification that receives majority of votes determines prediction made by our model. The Random Forest Classifier uses a simple yet effective core algorithm. In data science, the random forest classifier model performs well because several closely related models (trees) working together will outperform any individual constituent models[39].

3. METHODOLOGY

India is an agricultural nation, and much of its prosperity depends on agricultural extension services and closely associated agricultural industry outputs. In Indian agriculture, the high level of inconstancy causes the farming to collapse. An agricultural development also depends on several soil factors and atmospheric gases, such as nitrogen gas, phosphorus, and potassium, crop rotation, ground moisture, exterior degrees, and climatic aspects such as temperatures and precipitation. Figure 4, represents the proposed system architecture.

3.1 Data Collection

The names of the states and districts, the crop-growth year, the area, the mass production, and the crop that has to be cultivated are all collected in the online dataset, refer figure 1.

	State_Name	District_Name	Crop_Year	Season	Crop	Area	Production
0	Andaman and Nicobar Islands	NICOBARS	2000	Kharif	Areca nut	1254.0	2000.0
1	Andaman and Nicobar Islands	NICOBARS	2000	Kharif	Other Kharif pulses	2.0	1.0
2	Andaman and Nicobar Islands	NICOBARS	2000	Kharif	Rice	102.0	321.0
3	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Banana	176.0	641.0
4	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Cashewnut	720.0	165.0
...	...	...	...	...	...	...	...
246086	West Bengal	PURULIA	2014	Summer	Rice	306.0	801.0
246087	West Bengal	PURULIA	2014	Summer	Sesamum	627.0	463.0
246088	West Bengal	PURULIA	2014	Whole Year	Sugarcane	324.0	16250.0
246089	West Bengal	PURULIA	2014	Winter	Rice	279151.0	597899.0
246090	West Bengal	PURULIA	2014	Winter	Sesamum	175.0	88.0

246091 rows × 7 columns

Figure 1. Crop production samples from different states of India in various years

```
# Checking missing values of the dataset in each column
crop_data.isnull().sum()

State_Name      0
District_Name   0
Crop_Year       0
Season          0
Crop            0
Area            0
Production      3730
dtype: int64
```

Figure 2. Checking missing values of the dataset in each column

```
# Checking missing values of the dataset in each column
crop_data.isnull().sum()

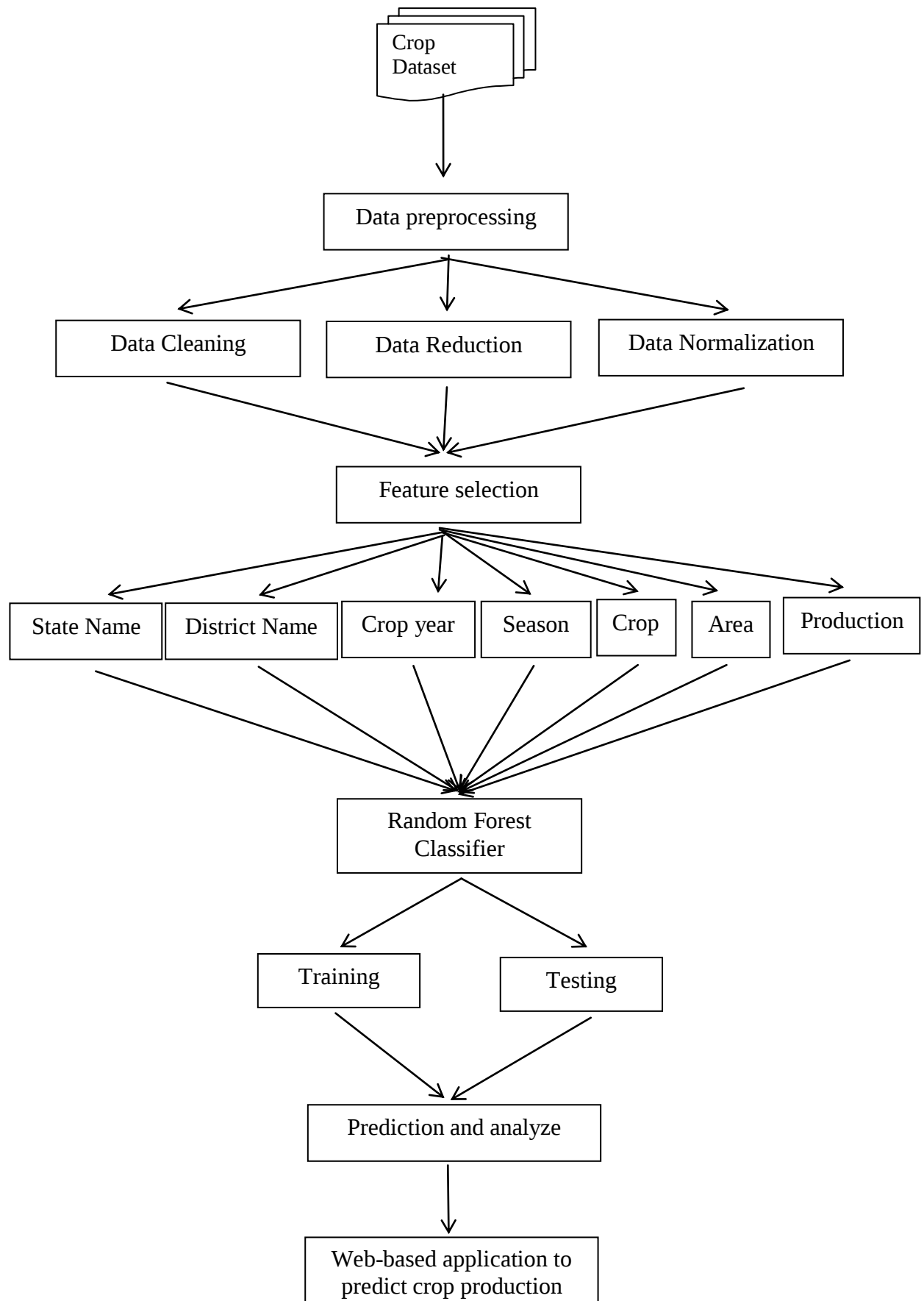
State_Name      0
District_Name   0
Crop_Year       0
Season          0
Crop            0
Area            0
Production      0
dtype: int64
```

Figure 3. Checking missing values after dropping null values

3.2 Data splitting

The entire dataset is divided into two halves, with, for instance, 25% of the data being put aside for model testing and the remaining 75% being utilized to train the

model. The dataset is next subjected to the random forest classifier in order to validate the data.

**Figure 4. Proposed system architecture**

3.3 Random Forest Classifier

The random forest classifier is an effective bagging method rather than a boosting method. In a random forest classifier, decision trees are processed simultaneously. These decision trees don't interact with one another. Finally, a graph was used to display the discrepancy between the output as expected and as real. Datasets are being gathered from various sources and stored in the data storage. The data are next sent to the preprocessing procedure, which entails the three processes of data cleaning, data reduction, and data normalization. The removal of erroneous and incomplete data occurs throughout the data cleansing process, refer figure 2 and figure 3. The digital information that is numerical or alphabetical is then transformed into a simpler form via data reduction. Finally, data normalization is used to convert the numerical columns' values into a uniform scale without altering the range of values' differences. Following feature selection and data extraction, the data are chosen. The feature selection approach entails either manually or automatically choosing the characteristics that are appropriate for the project result. Data extraction is the

process of removing data from a data storage system so that it may be processed further. The random forest classifier then boosts prediction accuracy and generates crop production as an output.

Dataset visualization, training, and testing modules are among the ones we're employing in this project. We are utilizing the pandas library file to load the basic datasets in the dataset module. The matplotlib package is then utilized in the visualization module to plot the arrays and graphs. The model then executes with the training input and generates the output in the training module. Last but not least, the test input in the testing module is a dataset used to evaluate the final model that was applied to the training input sample. These modules are used by the suggested system to obtain the output for the production graph.

4. RESULTS

The Proposed system predicted values on the test dataset, compared to actual values is shown in figure 5. Random forest has got an accuracy 90 percent, whereas it is a bit slower. A web based user interface application is created for friendly usage, home page is shown in figure 6.

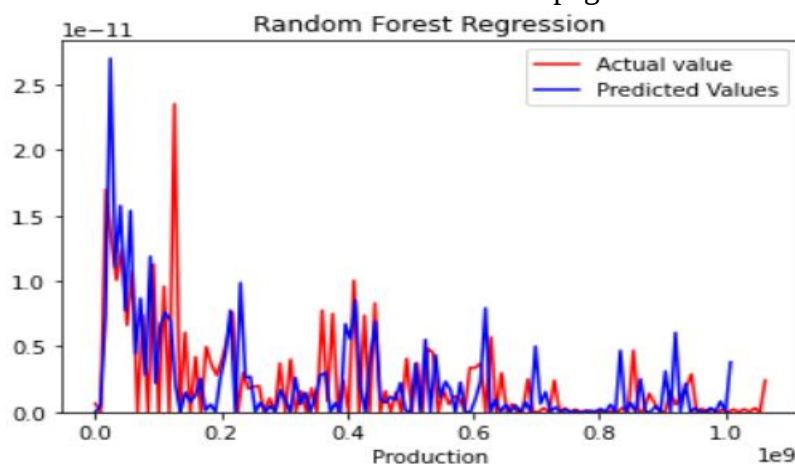


Figure 5. Actual values and predicted values achieved by the proposed system

Automated Crop Yield Prediction

Select the fields

Select Sate:

Select District:

Select Season:

Select Crop:

Figure 6. Web based automated crop yield prediction system home page

5. CONCLUSION

India is an agricultural nation, and much of its prosperity depends on agricultural extension services and closely associated agricultural industry outputs. Farmers used to estimate crop yield based on their past experiences and reliable historical data and then make important cultivation decisions in accordance with the predictions. Machine learning (ML), the subset of Artificial Intelligence (AI) which focus on learning, is a useful method that can estimate yields more accurately utilizing a variety of characteristics. For accurate crop yield prediction, RF Classifier is used in our research work. Random forest has got accuracy 90 percent, whereas it is a bit slower. A web based user interface application is created for friendly usage.

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