

CROP YIELD PREDICTION USING MACHINE LEARNING ALGORITHM FOR SUSTAINABLE AGRARIAN APPLICATIONS

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ABSTRACT:

Due to the fact that agriculture produces a significant amount of the world's food supply, it is one of the topics of interest that the public is most focused on. India's frugality is primarily influenced by the agricultural industry. The majority of India's agricultural crops are constantly adversely impacted by changes in the global environment. An extremely important and challenging task before cultivation is predicting the crop yield based on the location and the season. The Random Forest Algorithm is used. It gives growers and manufacturers a way to promote their products effectively and a technique to anticipate crop yields before planting. Deep reinforcement learning creates a comprehensive crop yield prediction framework that can transfer the raw data to the crop prediction values by combining the intelligence of reinforcement learning and deep learning. The dataset is used as the input. In the end, the experimental results display the accuracy rating and project the crop yield.

INDEX TERMS:

Crop yield prediction, deep recurrent Q-network, deep reinforcement learning, intelligent agrarian application.

INTRODUCTION:

Agriculture produces the majority of the world's food, it is one of the areas of interest. Due to a shortage or lack of food, famine is currently occurring in several nations. A convincing method to eliminate shortages is to increase food production. The stated and most significant goals of the United Nations are to increase food security and decrease hunger by 2030. Therefore, it is essential for the world's food production that crop protection, land mapping, and crop yield forecasts are done. Since the advent of tools for mechanical learning (ML), information science, and neuroscience, agriculture has become a significant trade partner. In order to enhance human health, agriculture tries to continuously improve agricultural yields and, therefore, crop quality.

Similar to an umbrella, machine learning contains crucial color theories and methods. The usage of machine learning with the Random Forest algorithm can be shown when examining excellent agricultural models. A well-liked machine learning algorithm is Random Forest. It has the ability to manage very huge data collections. To extract potential knowledge from the information already accessible, data scientists employ a variety of machine learning methods.

Since a significant percentage of the food that society consumes is produced by the agricultural sector, it is one of the major areas of interest to society. Currently, an increasing population combined with a shortage or absence of food causes famine in many countries. Increasing food production is a powerful way to end starvation. By 2030, the United Nations must achieve two important goals: increasing food security and reducing hunger. Therefore, crop protection, land evaluation, and crop yield forecast are of more significant importance to the production of food globally [1].

The ability of a nation's policymakers to analyze exports and imports appropriately and strengthen national food security rests on accurate forecasting. The forecast of yield helps cultivators and farmers make financial and management decisions. To establish the level of food security in a region, agricultural supervision, especially the observation of crop productivity, is essential [2]. On the other hand, crop yield forecasting is extremely difficult due to a number of complex factors. Crop yield is largely influenced by climate factors, soil quality, landscapes, insect infestations, water availability and quality, genotype, and other factors [3] – [5]. The agricultural yield processes and tactics change over time, are deeply non-linear in nature [6], complex as a result of the integration of numerous associated components [7], [8], and are influenced by non-arbitrate runs and outside causes.

Typically, a significant portion of the agricultural framework cannot be defined in a simple stepwise computation, especially when dealing with complex, imperfect, confusing, and vehement datasets. Numerous research show that machine learning algorithms have comparable higher potential than traditional statistics at this time [9] - [12]. Machine learning is a subfield of artificial intelligence that allows for the instruction of computers without explicit programming. These procedures address agricultural frameworks that are either non-linear or linear in nature with astounding predicting accuracy [13]. The strategies used in machine learning agriculture frameworks are developed through the learning process. To do a certain activity, these processes require excessive training. The model creates assumptions to test the data when the training process is over.

Additionally, machine learning is similar to an umbrella that covers several important approaches and techniques. We can see that artificial and deep neural networks are used in the most popular agricultural models [14]. Deep learning is a branch of machine learning that may produce results from different combinations of raw data. By using a decade's worth of field data, deep learning algorithms, for instance, can create a probability model that offers insights into how crops perform in various climatic situations [15]. Data scientists use a variety of machine learning methods to extract useful information from the data at hand. Reinforcement learning is a fascinating subfield of artificial intelligence [16]. These might be considered to be a key class of algorithms that can be used to simplify logic in dynamic programming. Machine learning models are prepared for decision-making using reinforcement learning [17]. The agent gains the ability to complete a task in an uncertain, potentially complicated environment. The environment rewards the agent's action based on it.

In this situation, the machine serves as the agent, while the environment around it serves as the setting. Deep reinforcement learning (DRL), a recent advancement in artificial intelligence, is a powerful tool for intelligent decision-making in a variety of fields, including energy management, robotics, health care, smart grid, game theory, finance, computer vision, natural language processing, sentiment analysis, and others. It combines a wide range of reinforcement learning techniques with deep learning models. [26, [27] This model has proven effective in handling a variety of challenging decision-making tasks that were previously out of the machine's capabilities. It is therefore recommended as a persuasive example for creating intelligent agricultural frameworks. Deep successor networks, multi-agent deep reinforcement learning, and deep Q-networks are examples of deep reinforcement learning defining models.

In this paper, we offer a deep reinforcement learning-based framework for supervised smart agriculture. The most profitable iterations of a deep Q-Learning based DRL algorithm are utilized to increase the accuracy of agricultural yield forecasts. Other deep learning algorithms, such as Autoencoders [28], Deep Belief Networks [29], Gaussian Bernoulli RBM's [30], Bayesian Neural Nets [31], and Deep Generative models [32], may not be constrained by biases or require significant manual labor in label formation. These models occasionally fall short of interpreting ambiguous inputs while taking uncertainty into account. The majority of these methods use sub-optimal greedy techniques, learning only one layer of features at a time without updating its lower-level parameters, which leads to slow and ineffective computations. The proposed effort addresses the aforementioned issues, advancing smart agriculture and increasing food production as a result.

LITERATURE SURVEY:

There are undoubtedly countless conceivable outcomes for future developments in artificial intelligence [33], [34]. Deep learning has exploded in tandem with tremendous data advancement for the purpose of opening up new opportunities [35]. This led to the need for better methods to plan, choose, and evaluate data-intensive tactics in agricultural settings [36], [37]. The prediction of crop yields can be viewed as a pattern identification issue where AI has demonstrated notably effective performance for agricultural applications [38]. The soil characteristics and tillage system should be considered for predicting potato crop output, according to Abrougui et al. The ANN model demonstrated excellent yield estimation potential [39].

Through the use of ANN, Haghverdi et al. have defined the prediction of cotton lint from crop phenology. To create 61200 models connecting to individual crop indices to field estimates of cotton production to be forecasted, the ANN technique is utilized [40]. According to the climate indices and the length of the precipitation, Byakatonda et al. explained an ANN-based yield forecast for the maize crop. It is possible to anticipate yield using ANN models, which simplifies agricultural planning [41]. The earlier-mentioned methodologies depended on feature extraction through time-domain and frequency-domain processing techniques, and ANNs were used for the processing in these approaches. A fixed-wing unmanned aerial aircraft (UAV) equipped with a digital camera and multispectral sensors was used to collect the datasets of RGB and multispectral images. The network's performance was compared to the conventional vegetation index-based method after being trained on various datasets. Additionally, the trained network's temporal and geographical generality was looked into. The findings demonstrated that for estimating rice grain yield during the ripening stage, CNNs trained on RGB and multispectral datasets outperform VIs-based regression models significantly. Deep CNN may be trained to recognize key spatial elements in the RGB imagery of very high spatial resolution that are relevant to the distribution of grain yield. The findings show that deep convolutional neural networks have the capacity to estimate rice grain yields with superior spatial and temporal generality and a wider forecasting time window.

Due to the shallow architecture of the ANN in learning the complicated non-linear interactions in the yield prediction system, manual feature extraction is limited in that it relies heavily on past knowledge of the data to predict yield. Such issues are somewhat addressed with the introduction of deep learning. To estimate the crop yield of the rice crop at the ripening stage, Yang et al. have suggested a deep convolution neural network model. From the high spatial resolution RGB image, the CNN network can infer the key spatial characteristics pertaining to crop yield [42]. The crop mapping approach used in VOLUME 8, 2020 86887 was made possible by deep learning to identify crop production. Crop Yield Prediction Using DRL Model for Sustainable Agrarian Applications in a Specific Region. D. Elavarasan and P. M. Durairaj Vincent.

The maps produced by the deep model allowed a map-to-map comparison with the CDL to show the areas of disparity. Northern Texas was used as an example where the winter wheat area of the CDL is significantly different from official numbers. Deep learning is an automated and reliable method for handling the seasonality of winter wheat variations without the need for labor-intensive ground data collecting or human feature engineering, as demonstrated by the visual representation of the deep model behaviors and recognized patterns. The suggested deep learning approach has a great deal of promise to close historical gaps in traditional sample-based classification and expand applicability to places where only regional statistics are available. It demonstrates the feasibility of producing maps exclusively from regional information. To fully utilize already-existing data and knowledge sources, the adaptable deep network architecture can be combined with different statistical datasets. [43]

The deep CNN and artificial neural networks are used by Zhong et al. to model the winter wheat mapping utilizing ground data and statistical references. This makes it possible to automatically identify wheat seasonality without needing samples [43]. Based on photos of sick leaves collected by image processing, Ramesh et al. [44] suggested an efficient deep neural network methodology to identify and categories crop yield. In order to estimate maize production, Babak et al. used the DSSAT model's inputs for irrigation and rainfall to build a numerical deep learning model of crop growth [45]. Using deep learning, an effective automatic approach for estimating the heading date of the rice crop yield Desai et al. have suggested CNN network utilizing time series RGB photos of the crop [46]. For estimating mango fruit yield, Koirala et al. suggested a two-stage deep learning technique utilizing CNN [47]. Adaptive crop feature extraction can be recognized by deep learning approaches by the hierarchical representation of DNN architecture, in contrast to ANN-based processes, which can effectively be identified as a primary predictor from the literature. DNN architecture, however, has a limited ability for generalization because it requires a lot of experience and background information.

As a result, it's crucial to organize a smart architecture based on deep reinforcement learning (DRL) to investigate agricultural yield prediction. In the DRL framework, reinforcement learning and deep learning give the agent the ability to discover the optimum approach for solving issues in the present [48]. The ability to generalize to a meta-learning environment is made possible by DRL [49]. DRL is a general technique for resolving optimization issues via trial and error, and it has applications in a number of industries, including agriculture [50], healthcare [51], energy management [52], robotic systems [53], and game theory [54]. The Deep Q-Network DRL algorithm and the suggested technique are introduced briefly in the section that follows. In order to manage crops, assess food security, trade, and make policy decisions, it is crucial to predict rice grain output before harvest. Utilizing remotely sensed products, such as the vegetation index (VI) from multispectral photography, crop yield estimation has seen several successful applications. However, VI-based methods only work well for estimating rice grain production at the midpoint of growth and are insufficient for determining grain yield at the point when the rice is ripening.

EXISTING SYSTEM:

In order to predict crop yield, the current model builds a Deep Recurrent Q-Network model, which is a Recurrent Neural Network deep learning algorithm atop the Q-Learning reinforcement learning algorithm. The stacked layers are arranged in order of thickness. When starting a recurrent neural network, data parameters from the data collection are typically used. The Q-learning network creates a setting that, in general, forecasts the crop production. The use of the input parameters affects this process. The recipient then earns an overall score for the executed acts. It is attained by maximizing forecast accuracy while also decreasing error.

PROPOSED SYSTEM:

The crop yield dataset from the dataset repository was used as input in this system. The data pre-processing phase must then be implemented. In order to ensure that we are correctly predicting, we must deal with any missing values or irrelevant values in this stage. The data must then be divided into test and train sets. In this step, the model is predicted using test data and evaluated using train data. Later, we must put machine learning techniques like the Random Forest method into practice. Last but not least, the experimental findings display the performance outcomes, including the accuracy rating and the anticipated crop output.

IMPLEMENTATION:

MODULES

- Data selection
- Data preprocessing
- Data splitting
- Training the model
- Performance Analysis

DATA SELECTION

• A data set repository like the Kaggle repository provided the input data.

• A crop yield dataset was utilized to put the model into practice.

• The dataset includes details on the location, crop name, season, region, and production.

• Python was utilized to carry out the project. We used the pandas package to load the data.

DATA PREPROCESSING

• Data preprocessing is nothing more than the preparation of data for use in implementation.

• At this point, the dataset is being cleaned up by removing any extraneous data.

• As part of this procedure, the dataset is also cleaned by deleting any corrupted or irrelevant data. As a result, the dataset's correctness rises, indirectly boosting the model's effectiveness.

- The two major actions performed here are,
    - Missing data removal
    - Standard scalar

Missing data removal: In this stage, 0 is used to replace null values such as Nan values.

Standard scalar: Every attribute's or variable's mean and scales are converted to unit variance in this stage. We eliminate all of the anomalies in our dataset by taking these actions.

DATA SPLITTING

• The role of the data in the machine learning process is highly important for the learning process.

• For assessing the effectiveness of the algorithm, we also need the testing data in addition to the training data.

• 85% of the crop yield dataset was used as training data for this model, and the remaining 15% was used as testing data.

• The act of breaking a dataset into two halves is known as data splitting. Cross-validation is generally done for this purpose. One of these two parts of the data is used to create the prediction model, while the other part is utilized to assess the model's effectiveness.

• It is crucial to ensure that the training dataset receives the majority of the data used for data splitting and the model testing dataset receives the smallest possible amount of data.

TRAINING THE MODEL

• In order to train the model, we must use the train data. Here, the model is trained and evaluated using the Random Forest Regression method.

•Multiple decision trees are used in the Random Forest Regression machine learning technique to learn the models.

• Rather than relying just on a single decision tree, we can readily predict the outcome in this case thanks to the many decision trees.

• The Random Forest technique is used to train the model, and following training, the model is prepared to predict values. After that, the model is applied to the test data to forecast the values.

RESULTS AND PERFORMANCE EVALUATION:

Data Selection

The data is selected from the below dataset,

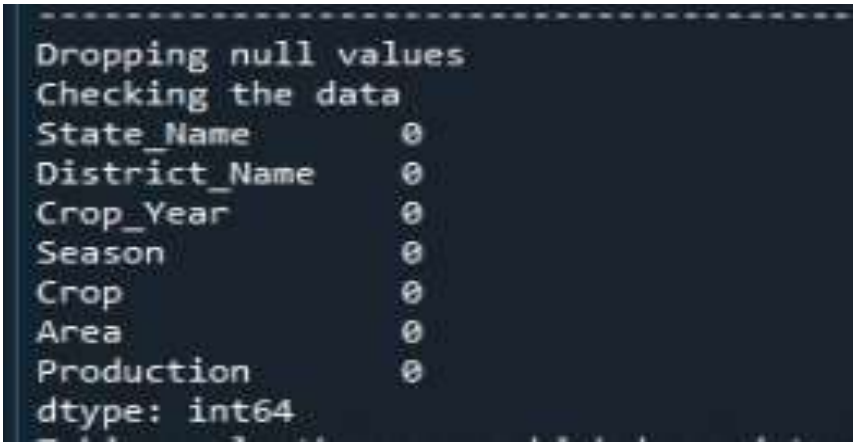
df - DataFrame

Index	State_Name	District_Name	Crop_Year	Season	Crop	Area	Production
0	Andaman and Nicobar Islands	NICOBARS	2000	Kharif	Arecanut	1254	2000
1	Andaman and Nicobar Islands	NICOBARS	2000	Kharif	Other Kharif pulses	2	1
2	Andaman and Nicobar Islands	NICOBARS	2000	Kharif	Rice	102	321
3	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Banana	176	641
5	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Coconut	18168	6.51e+07
6	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Dry ginger	36	100
7	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Sugarcane	1	2
8	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Sweet potato	5	15
9	Andaman and Nicobar Islands	NICOBARS	2000	Whole Year	Tapioca	40	169
10	Andaman and Nicobar Islands	NICOBARS	2001	Kharif	Arecanut	1254	2061
11	Andaman and Nicobar Islands	NICOBARS	2001	Kharif	Other Kharif pulses	2	1
12	Andaman and Nicobar Islands	NICOBARS	2001	Kharif	Rice	83	300

FIGURE 1: DATA SELECTION

Data Preprocessing

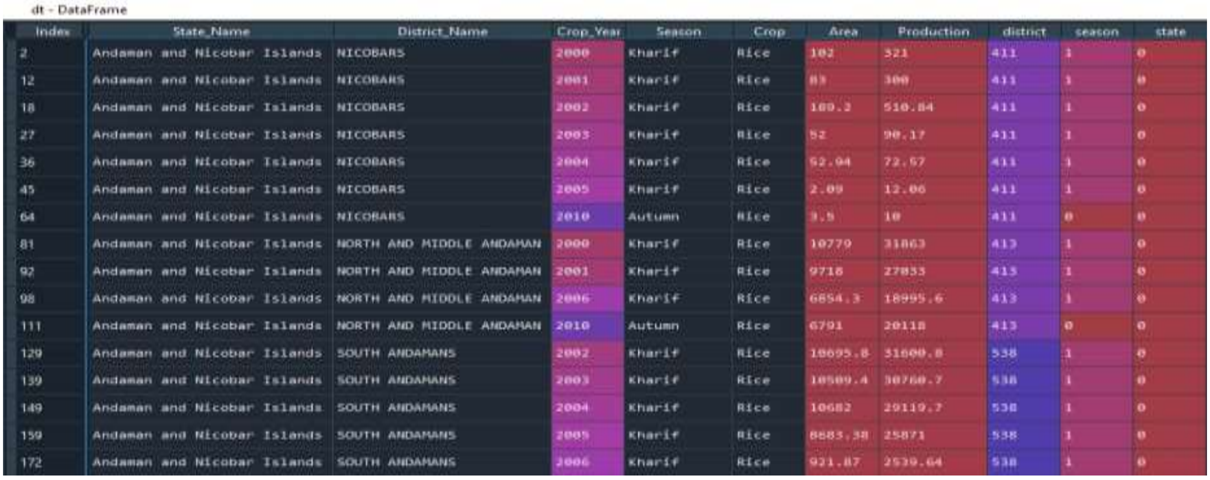
Missing values are removed and the count of missing values becomes 0.



```
Dropping null values
Checking the data
State_Name       0
District_Name    0
Crop_Year        0
Season           0
Crop             0
Area             0
Production       0
dtype: int64
```

FIGURE 2: MISSING VALUES

Standard scalar is performed by encoding the state and district names to digits.



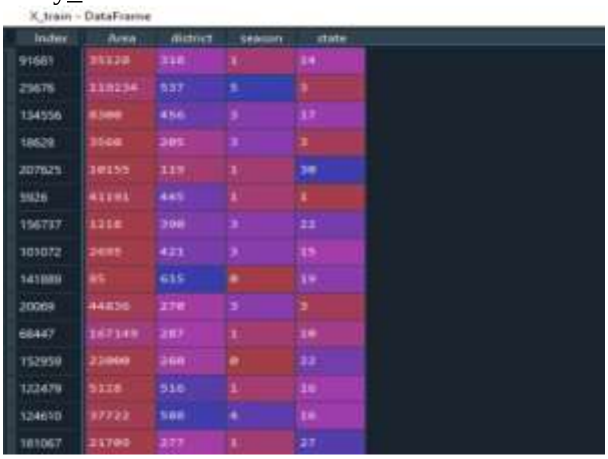
dt - DataFrame

Index	State_Name	District_Name	Crop_Year	Season	Crop	Area	Production	district	season	state
2	Andaman and Nicobar Islands	NICOBARS	2000	Kharif	Rice	102	321	411	1	0
12	Andaman and Nicobar Islands	NICOBARS	2001	Kharif	Rice	83	300	411	1	0
18	Andaman and Nicobar Islands	NICOBARS	2002	Kharif	Rice	189.2	510.84	411	1	0
27	Andaman and Nicobar Islands	NICOBARS	2003	Kharif	Rice	52	90.17	411	1	0
36	Andaman and Nicobar Islands	NICOBARS	2004	Kharif	Rice	52.94	72.57	411	1	0
45	Andaman and Nicobar Islands	NICOBARS	2005	Kharif	Rice	2.09	12.06	411	1	0
64	Andaman and Nicobar Islands	NICOBARS	2010	Autumn	Rice	3.5	10	411	0	0
81	Andaman and Nicobar Islands	NORTH AND MIDDLE ANDAMAN	2000	Kharif	Rice	10779	31863	413	1	0
92	Andaman and Nicobar Islands	NORTH AND MIDDLE ANDAMAN	2001	Kharif	Rice	9718	27833	413	1	0
98	Andaman and Nicobar Islands	NORTH AND MIDDLE ANDAMAN	2006	Kharif	Rice	6854.3	18995.6	413	1	0
111	Andaman and Nicobar Islands	NORTH AND MIDDLE ANDAMAN	2010	Autumn	Rice	6791	20118	413	0	0
129	Andaman and Nicobar Islands	SOUTH ANDAMANS	2002	Kharif	Rice	10695.8	31600.8	538	1	0
139	Andaman and Nicobar Islands	SOUTH ANDAMANS	2003	Kharif	Rice	10509.4	30760.7	538	1	0
149	Andaman and Nicobar Islands	SOUTH ANDAMANS	2004	Kharif	Rice	10682	29119.7	538	1	0
159	Andaman and Nicobar Islands	SOUTH ANDAMANS	2005	Kharif	Rice	8683.38	25871	538	1	0
172	Andaman and Nicobar Islands	SOUTH ANDAMANS	2006	Kharif	Rice	921.87	2539.64	538	1	0

FIGURE 7.3: STANDARD SCALER

Data splitting

Data is split into two sets namely training and testing data. In this we have x_train data, y_train data, x_test data and y_test data.



X_train - DataFrame

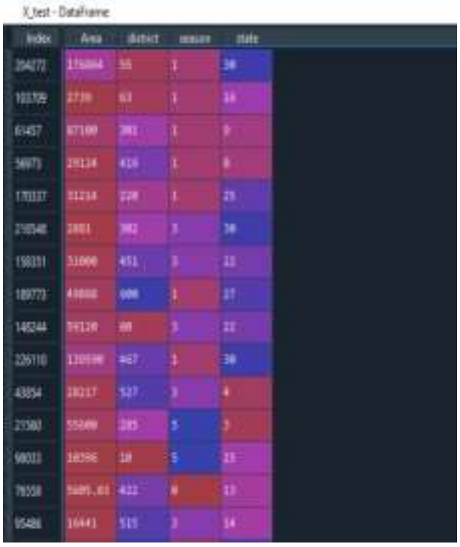
Index	Area	district	season	state
91681	35120	318	1	14
25676	110234	537	5	5
134556	6300	456	3	17
18628	3500	285	3	3
207625	10155	119	1	30
5926	41191	445	1	1
156737	1210	308	3	22
101072	2695	421	3	15
141889	85	615	0	19
20069	44836	278	3	3
68447	167149	287	1	10
152959	23000	268	0	22
122479	5118	516	1	16
124610	37722	508	4	16
181067	21700	277	1	27

y_train - Series

Index	Production
91681	119048
25676	161235
134556	21000
18628	5973
207625	18208
5926	124889
156737	2700
101072	8925
141889	181
20069	87886
68447	618000
152959	6000
122479	3942
124610	26638
181067	82523

FIGURE 4: X_TRAIN DATA

FIGURE 5: Y_TRAIN DATA

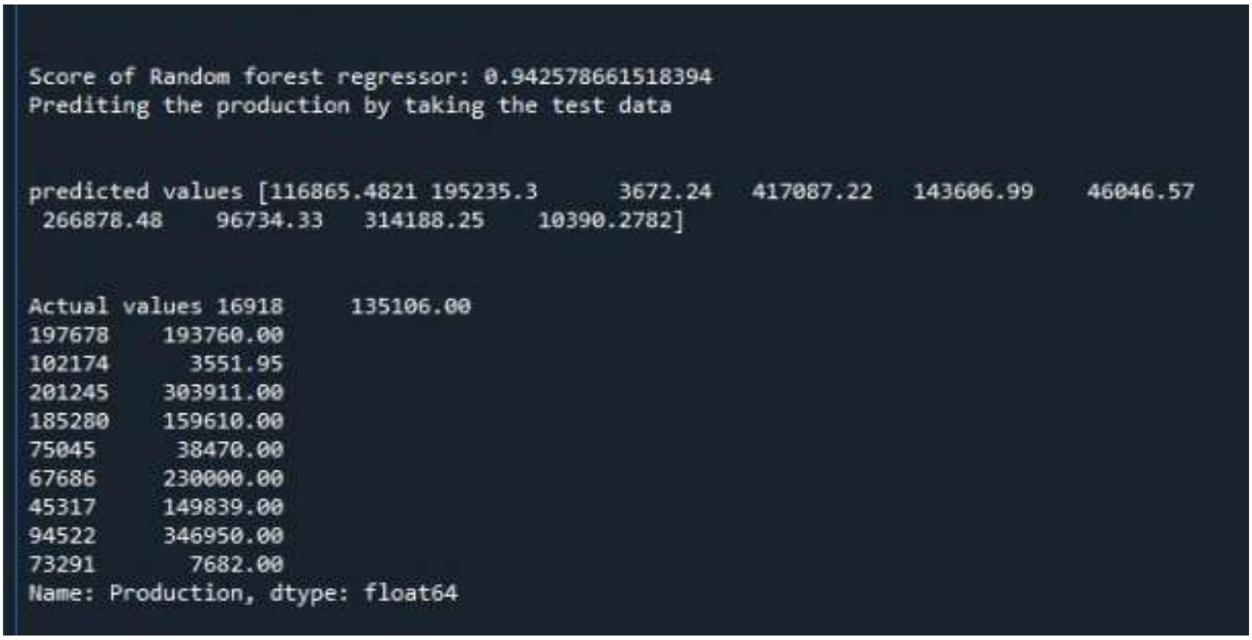


y_test - Series

Index	Production
204272	420936
103709	874
61457	201300
56973	76689
170337	59881
218548	5906
158351	70000
189773	190899
148244	141439
226110	274294
43854	34215
21560	122895
98033	31207
76558	3968.67
95486	52677

FIGURE 6: X_TEST DATA FIGURE 7: Y_TEST DATA

Random Forest Algorithm



```
Score of Random forest regressor: 0.942578661518394
Prediting the production by taking the test data


predicted values [116865.4821 195235.3      3672.24    417087.22    143606.99    46046.57
 266878.48    96734.33   314188.25    10390.2782]


Actual values 16918      135106.00
197678     193760.00
102174       3551.95
201245     303911.00
185280     159610.00
75045       38470.00
67686      230000.00
45317      149839.00
94522      346950.00
73291        7682.00
Name: Production, dtype: float64
```

FIGURE 8: ACCURACY_SCORE

Visualization:

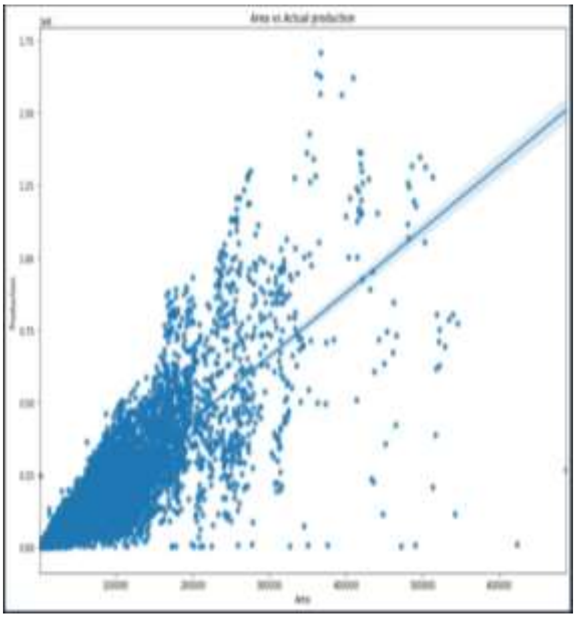


FIGURE 9: AREA VS ACTUAL FIGURE GRAPH

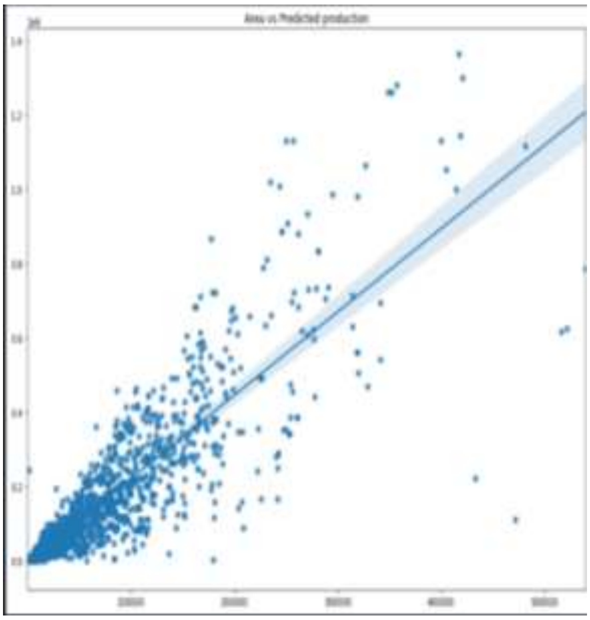


FIGURE 10: AREA VS PREDICTED PRODUCTION GRAPH

CONCLUSIONS AND FUTURE WORKS:

CONCLUSION:

This system was proposed for the detection of the crop yield in an effective way using the machine learning algorithms like Random Forest algorithm. The analysis of the experimental results has shown that the proposed model produces an efficient and effective results when compared to the results obtained from the reinforcement learning algorithm. Thus, the proposed model predicts the crop yield with an outstanding accuracy compared to the reinforcement learning model.

FUTURE WORK:

In future we can also consider the data that contains the information about the conditions of the weather, soil etc. which will be obtained from the datasets that are published from the trusted websites. In future the model can be modified by even considering the maximum depth of the decision trees. The type of the dataset also affects the analysis therefore, more cleaned and preprocessed data can be used which may produce a great result.

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