Prediction of Agricultural Crop Price and Machinery Rental Price using Machine Learning Algorithms

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Abstract- **Agriculture is a vital sector that contributes significantly to the global economy. However, the agriculture industry faces several challenges, including unpredictable fluctuations in crop prices and the unavailability of farming equipment. Maximum accuracy in predictions of crop prices and equipment rental prices can help farmers and agricultural businesses make informed decisions, improve profitability and productivity, and optimize their decision-making processes. Features like market, location, and variety are used to predict crop prices so that farmers can easily know the corresponding prices according to the market and choose to sell for a better price in a better place. Owning and maintaining machinery for temporary work is risky, and most of the farmers choose a rental business, as a result, demand for machinery rental got raised and holders started to rent their machines to fulfill it. This led to the challenge of finding equivalent profit for both lenders and buyers. The intention of the study is to furnish better price prediction for both crops and machinery rental using machine learning algorithms like Random Forest, Decision Tree Regression, Linear Regression, and Gradient Boosting. The performance computation of the regression models exposed that Decision Tree and Linear Regression perform better for crop price prediction and machinery rental price prediction respectively than the other models considered in this study. Finally, these two algorithms are used to build a user-friendly interface.**

Index Terms- **Agriculture, Machinery rental, Regression model, Machine learning algorithms, Crop price prediction.**

I. INTRODUCTION

India has a largely agrarian economy. The classification of the country's land as an agricultural field is 54%. A large portion of India's capital income, which is primarily required for building projects, industrial development, and the upgrading of public services, comes from agriculture. Moreover, the agricultural sector provides work for 151 million people nationwide, or roughly 60% of the Indian population, and it accounts for nearly 18% of India's GDP. India's agriculture sector had remarkable expansion over the last 6 to 7 years, with an average annual growth rate of 4.6%. The agricultural industry in India almost entirely drives the country's economic growth, hence expanding the agricultural sector is crucial to India's economy. There are advantages and disadvantages in agriculture, with the main negatives creating considerable challenges for the farmer who play a significant part in the sector. The proposed research article offers two modules for agriculture which are crop price prediction and machinery rental price prediction to address these issues.

The agricultural machinery market in India is expected to grow by about INR 1,852.6 billion by the year 2028, or about 10.5% more than it did. The market size in 2022 was INR 1,023.2 billion. Thus, obtaining and maintaining agricultural equipment for temporary labor is challenging. The agricultural machinery rental price forecast in our research report is crucial in determining the best course of action for the farmer's issue.

A lack of long-term production and consumption elasticity causes the price of agricultural commodities to be unstable and erratic. Crop prices can change due to market supply, demand, or both changes, there is a need for beforehand price prediction to overcome these fluctuations. Predicting the crop price by comparing all the market prices across the entire nation is one way to handle this problem, but it is also a huge challenge for both sellers and buyers to determine a fair crop price, which is our main objective.

Our system aims to develop a predictive model for crop prices and agricultural machinery rent prices using various machine-learning algorithms. Specifically, the comparison was made on the results of Random forest, Gradient boosting, Linear regression, and Decision tree to identify the leading algorithm with greater prediction accuracy. Additionally, we build a user-friendly front-end using Flask, HTML, CSS, and Bootstrap templates and used Sqlite3 as a database. The developed models are trained and evaluated on historical data to ensure high prediction accuracy. Our findings suggest that the Decision tree performs better for crop price and Linear regression performs better for machinery rental price than the other regression models considered in this study. The developed front end can be easily integrated with any existing system, providing an intuitive and user-friendly interface for end-users, which is a small contribution to the agriculture sector.

The upcoming sections of the paper explain about previous research review in section II, the project methodology in section III, evaluated results and analysis in section IV, and finally concluded the research idea.

II. LITERATURE SURVEY

Machine learning algorithms are popular for prediction and classification. We used the survey on literature review which showed that more preference was given for Neural network-based algorithms and Decision tree regression because the outcomes of these are better compared to other algorithms used in the work [1].

Researching the operations, performance, and business model of an ordinal rental service at the farm level is necessary for the prediction of machinery rental prices. The study that S. Singh [2] has suggested for Punjab does manual research on companies that rent out farm machinery. As a result of providing village farmers with loans and fertilizer, Primary Agricultural Credit Societies (PACS), which were offered by the Punjab State Farmers' Commission (PSFC), had more farmer connectivity than private entrepreneurs. Manual prediction can result in better decisions, but it takes time and can be challenging to apply to many agencies.

According to a study proposed by Khodabakhshian Rasool et al. [3] reports that the Kavardeh agriculture company developed the Preventive Maintenance Programme (PMP) in Iran, which is based on the number of hours that equipment is used when it is rented out and considers the R&M costs invested on representative tractors such as MF-285, JD-3350, and JD-3140. Knowing the different types of machinery and how they affect the soil can provide a farmer with a better understanding of the cultivation techniques to use and the equipment to get better results, which can then be used to determine the key parameters for the forecasting model [4].

Similar to machinery, the type of crop planted and the cultivating land affect crop prices. The trial was conducted on wheat, jute, potatoes, and three different types of rice. Previous research has shown that land properties like fertility, structure, and water availability are known before cultivation so the crops which are suitable to the particular land condition can grow with increasing quality and quantity [5]. Data analytics can help to know about crop and their benefits before sowing and helps in selecting the right crop. Originally, farmers were cultivating the crops based on their experience growing that crop on the field, but in recent days, farmers are rapidly cultivating the forced crops due to fluctuating market demands [6].

The agriculture sector exhibits a significant impact in the change from traditional prediction to an automated decision because machine learning has a variety of technology to aid in farming [7]. In order to anticipate the crop price accurately, data must be collected, and this can be done from a variety of sources [8]. Farmers may plan, schedule, and manage crop cultivation with the aid of features including crop kind, location, prior rainfall, WPI data, and export variables [9]. They can choose moral crops [11]-[12] and options for customers that can please customers in more contexts [13] by predicting the price for the upcoming year (next 12 months) [10] and being aware of upcoming market volatility. It can also help poor knowledge-farming people to ride an accurate path and can reduce the suicide rate due to the loss of their investment [14].

Every farmer needs to understand the use and manage water for agriculture wisely, which is the cardinal source for agriculture [15]-[16]. IOT has advanced technology to assist farmers in irrigation. Reference [17] explains smart/precision farming using IoT [18].

The aforementioned works all demonstrated that statistical methods produce superior results. However, the study conducted by Sabu et al. [19] on the prediction of areca nut prices in Kerala explains how Long Short-Term Memory (LSTM) performed better.

The model proposed by Zhang et al. [20] selected twenty-nine characteristics for the prediction model and implemented a suitable redundancy-lowering technique, namely the Minimum Redundancy & Maximum Relevance approach. Feature selection plays a significant role in providing high accuracy. Crop output is influenced by the sort of market the farmer utilized to sell his crops, since prices differ between markets, taking this factor into account when predicting prices can produce accurate findings [21]-[22].

Different kinds of models had been applied for predicting the prices of agricultural crops and machinery as shown below in Table.1, in this paper, we are considering Decision Tree Regression, Linear Regression, Gradient Boosting, and Random Forest to check for better accuracy.

Table.1. Previous Price Prediction Model and their Accuracy

Author	Algorithm	Better Accuracy Model
Khodabakhshian Rasool et al. [3]	Linear Regression & Random Forest.	Random Forest
M. T. Shakoor et al. [5]	K-Nearest Neighbor [KNN], Decision Tree Learning [DTL], & ID3	DTL & ID3.
S. Pandit et al. [6]	Linear Regression, XG Boost, DTL, & Nearest Neighbor [NN].	XG Boost
Rakhra Manik et al. [7]	NN & DTL.	Both
Neeraj Soni et al. [8]	DTL & Random Forest.	DTL
Ranjani Dhanapal et al. [9]	DTL.	DTL.
Madhuri Shripathi Rao et al. [10]	DTL, KNN, & Random Forest.	DTL
Ishita Ghutake et al. [11]	Random Forest & DTL.	DTL
G. S. Kakaraparthi et al. [12]	DTL	DTL
R. Rohith et al. [13]	DTL, & Support Vector Regression	DTL
S. Vijayasree et al. [14]	KNN.	KNN

R. Bhavani et al. [15]	Naïve Bayes, KNN & Support Vector Machine [SVM].	KNN
Zhang et al. [17]	Artificial neural network [ANN], SVM, Extreme learning machine [ELM], & Random Forest.	Random Forest
Yung-HsinPeng et al. [18]	Autoregressive integrated moving average, ANN, Partial least square, & RSMPLS.	Partial least square & ANN.
Wu et al. [19]	NN.	NN

III. METHODOLOGY

The proposed system consists of five sub-modules namely, Dataset collection, Data pre-processing, Model selection, Model Evaluation, and User interface as shown in Figure.1.

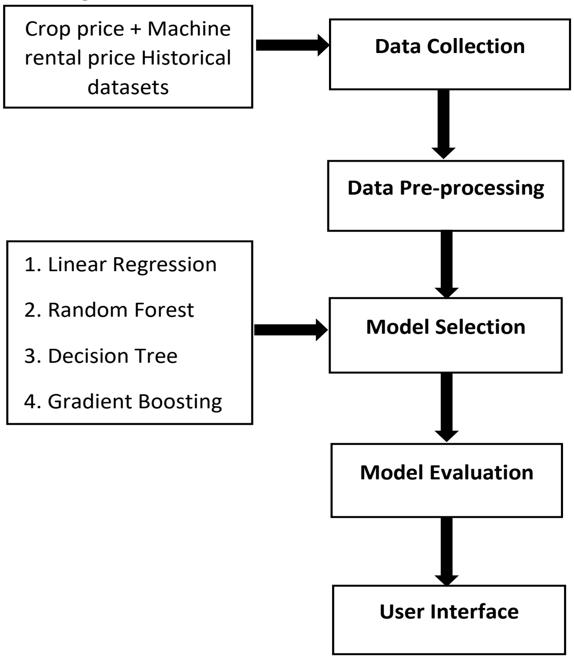

Fig.1. System Design Architecture

The phases of system architecture start by gathering information from many sources to aid in decision-making. It contains the essential elements that have the biggest impact on predicting crop price and equipment rental prices. The unstructured data was then processed during the succeeding pre-processing stage and transmitted in a better format. The completed structured datasets are then forwarded to the modelling step, where we decide the efficient model between Gradient boosting, Decision trees, Random forests, and Linear regression. Move on to the model evaluation calculating Root Means Square Error (RMSE), Mean Absolute Error (MAE), and R-squared (R2) value to generate the visualization of the model performance and finally build the user-friendly interface to help the farmers and also the rental business. The below subsections explain the complete methodology.

Phase 1: Data Collection

Since not all data could be gathered from a single source, it must be combined from various sources and prepared to facilitate decision-making. The proposed system datasets are collected from Data.Gov. and kaggle.com [23]. The chosen datasets include the key features that have the greatest influence on forecasting crop price and machinery rental which are shown in Table.2 and Table.3. The prediction of crop prices is currently more specialized and datasets are readily available on government platforms, but the rental price datasets for machinery are not as easily accessible on a single platform. Crops are taken from low-priced Potato to high-priced Arecanuts (i.e. from 5 to 50000 rupees) and we have calculated machinery rental cost based on the hours of rental usage. Some of the sources were structured, while others had unstructured data, which was transformed into a better form during the subsequent pre-processing phase.

Table.2. Features used in the Crop Price dataset

Features used in crop price prediction	
Feature	**Description**
Commodity	Name of the commodity.
State	State which crop market belongs.
District	District to which crop market belongs.
Market	Name of the market.
Min_price	The minimum price for the commodity.
Max_price	The maximum price for the commodity.

Modal Price	Current commodity price.
Date	Date to know the historical prices.

Table.3. Features used in the Machine Rental Price dataset

Features used in machinery rent price prediction	
Feature	**Description**
Machinery name	Name of the machinery.
Type	Type of agriculture the machinery used.
District	The district where the machinery belongs.
State	State where the machinery belongs.
Fuel Type	Type of the fuel used for the machine.
Engine Power	Engine power in HP.
Hourly rent	Rent for the machinery per hour.

Phase 2: Data Preprocessing

Pre-processing comes after data collection and is a crucial stage. For the crop and machine rental datasets, data cleaning has been carried out by removing null and noisy values, and data is visualized using a histogram graph. Inconsistent fields were present, so the found outliers were removed and used only relevant data, to increase the accuracy. Following data cleaning, the fields that were unrelated to the modelling and had a high degree of correlation with other fields were removed. The library function one hot encoder was used to convert certain of the features, such as commodity and market in crop datasets and machine name, district, and fuel type in machinery datasets, from categorical to numerical form. Sent to the modelling phase are the final structured datasets.

Phase 3: Model Selection

Since we were unsure which model would best predict the prices for crop and machine rental, many machine learning algorithms can be used for regression. We have settled on techniques like gradient boosting, decision trees, random forests, and linear regression. The datasets are divided into validating, testing, and training sets. The test set is used to calculate the generalization error of the final selected model after the generalization error of the validation set and training set are calculated.

The employed algorithms are:

1. Linear Regression:

A dependent variable is predicted using the other independent variables to calculate the crop and machine rental prices. It aims to find the best-fitting line that represents the relationship between the feature and the price. Removing the outliers from the model will lead to a successful reconstruction. The linear regression line that most closely resembles the data will also be the least erroneous one. It calculates the distance between them to decrease the discrepancy in accuracy between the expected and actual values.

The straightforward linear regression is shown in Eq.(1)

$$Y = aX + b \tag{1}$$

where Y is the dependent variable, a is the determined slope, X is the independent variable, and b is the determined intercept.

2. Random Forest:

An ensemble learning system called a random forest constructs several decision trees and then aggregates the results to generate a prediction. The average of all the decision trees' predictions is used to determine the final prediction. This method works by building numerous decision trees and using multiple lowers the danger of overfitting during training. Overfitting occurs when the data is fitted so closely to the sample

Hyperparameter tuning, where we can adjust the parameters and improve accuracy, is a crucial step in the model selection process. Analysis of Figure.2 and Figure.3 leads us to the conclusion that selecting more than 10 trees for both predictions improves accuracy.

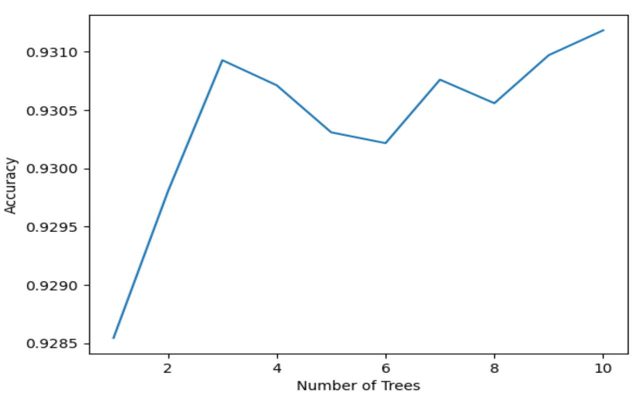

Fig.2. Hyperparameter tuning in Random Forest for crop dataset

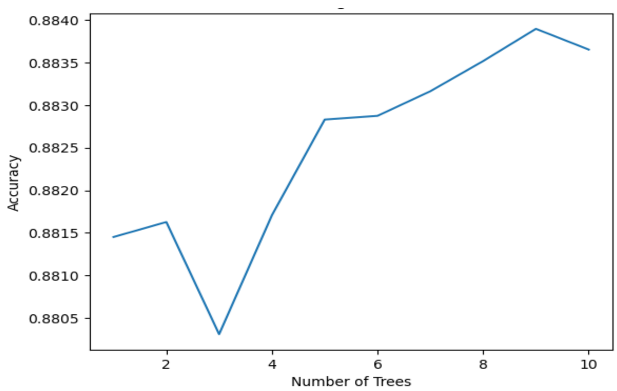

Fig.3. Hyperparameter tuning in Random Forest for machinery dataset

3. Decision Tree:

A supervised learning technique called a decision tree creates a tree-like model of decisions and potential outcomes. It divides the data at each node based on the feature yielding the largest information gain after starting with a root node representing the complete dataset. By following the branch of the tree that corresponds to the features of the input data, the final prediction is made. We can determine the Max-depth value, which provides the best accuracy by analyzing Figure.4 and Figure.5.

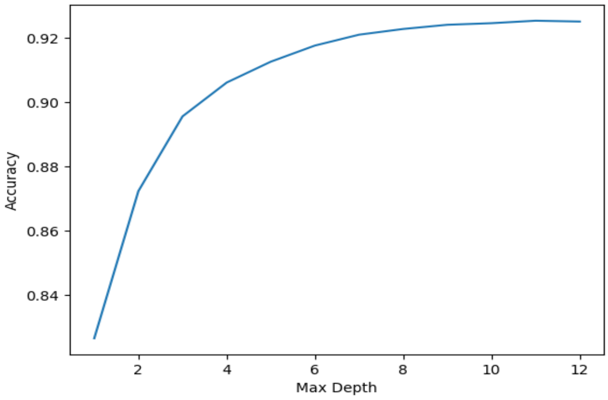

Fig.4. Hyperparameter tuning in Decision Tree for crop datasets

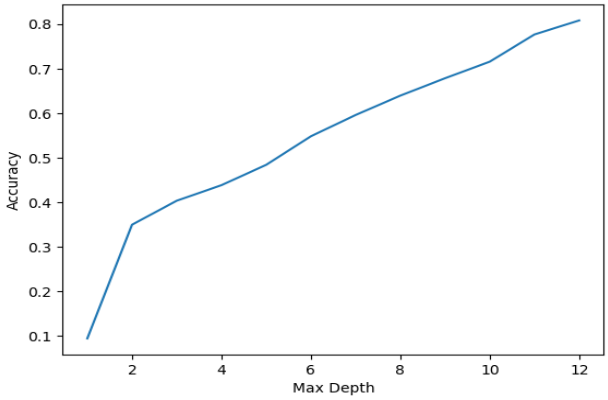

Fig.5. Hyperparameter tuning in Decision Tree for Machinery datasets

4. Gradient Boosting:

An ensemble learning approach called gradient boosting turns several weak learners, such as decision trees, into powerful learners. Combining all of the weak learner's outputs yields the final prediction. After loading the data into the base model, which could be the average regression model, we'll calculate the residuals by deducting the predicted values from the observed values, then build a residual model to remove errors and this process will continue until the residual is reached or the error is zero.

As we can see, for the best results, we should use n-estimators above 100 for the crop dataset and machine dataset as in Figure.6 and Figure.7.

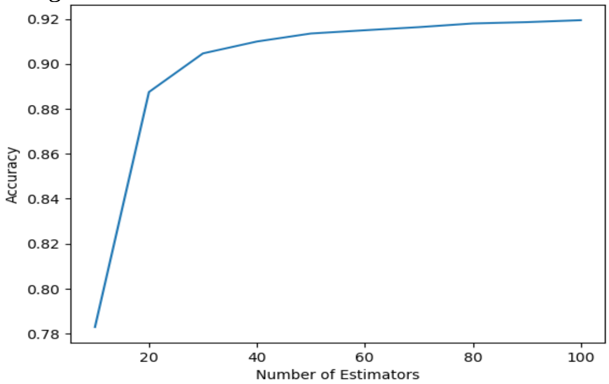

Fig.6. Hyperparameter tuning in Gradient Boosting for crop datasets

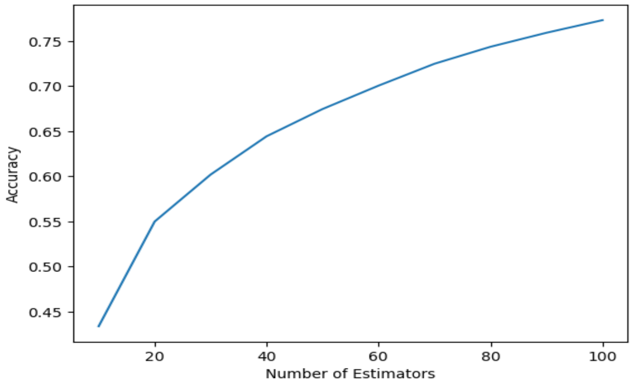

Fig.7. Hyperparameter tuning in Gradient Boosting for Machinery datasets

We analyzed hyperparameter tuning for both crop price and machinery rental price models in the case of all four algorithms and applied suitable values to get better accuracy.

Phase 4: Model Evaluation

This module is responsible for evaluating the trained models using appropriate performance metrics such as RMSE, MAE, and R2 score. The module should also be able to generate visualizations of the model performance.

The MAE is calculated using the below Eq.(2)

$$MAE = \frac{\sum_{k=1}^{s} |\mathrm{m_k} - n_k|}{s} \qquad (2)$$

Where m is the predicted price variable, n is the actual price variable, and s is the sample size.

The RMSE is calculated using the below Eq.(3)

$$RMSE = \sqrt{\frac{\sum_{k=1}^{s} (\mathrm{m_k} - n_k)^2}{s}} \qquad (3)$$

Where m is the predicted price variable, n is the actual price variable, and s is the sample size.

The R-Squared value is calculated using the below Eq.(4)

$$\mathrm{R - Squared} = 1 - \frac{\sum_{k=1}^{s} (\mathrm{o_k} - \hat{o}_\mathrm{k})^2}{\sum_{k=1}^{s} (\mathrm{o_k} - \bar{\mathrm{o}}_\mathrm{k})^2} \qquad (4)$$

Where o is the actual price variable, $\hat{o}$ is the predicted price variable, $\bar{o}$ is the mean value and s is the sample size.

Phase 5: User Interface

The system must have an intuitive user interface that enables users to enter information about crop type, location, and machinery before providing predictions in an easy-to-understand manner. This could be in the form of a web application or mobile application. Two of the well-performed algorithms for Crop price and Machinery rental price prediction are chosen for the web interface to display the result. The system used HTML, CSS, Flask, and JavaScript for the beautiful and working interface.

IV. RESULTS AND DISCUSSION

The outcomes of the machine learning algorithms were calculated based on various metrics such as Accuracy, Execution time, MAE, MSE, and R2 scores. The evaluation was done on a test dataset that was separate from the training dataset.

Crop Price Prediction

The proposed model uses four different algorithms for the prediction of crop prices, below graphs display the performance of all four algorithms, which is plotted using predicted crop prices in the y-axis and actual crop prices in x-axis.

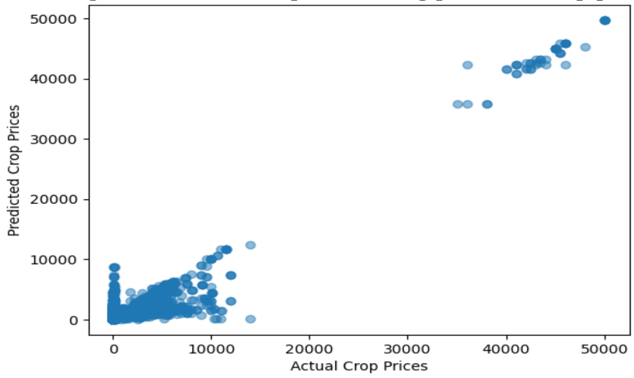

Fig.8. Random Forest performance for Predicted and Actual crop prices.

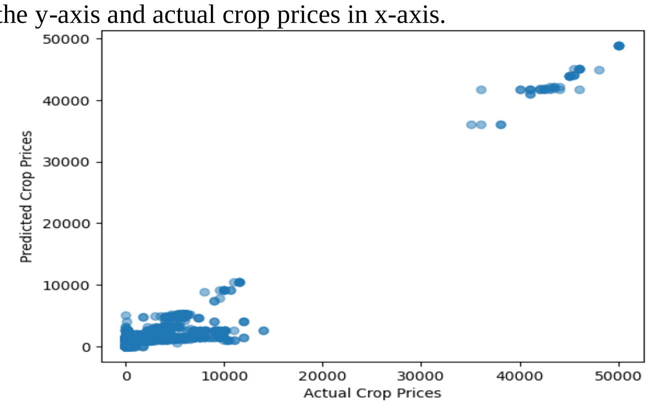

Fig.9. Gradient Boosting performance for Predicted and Actual crop prices.

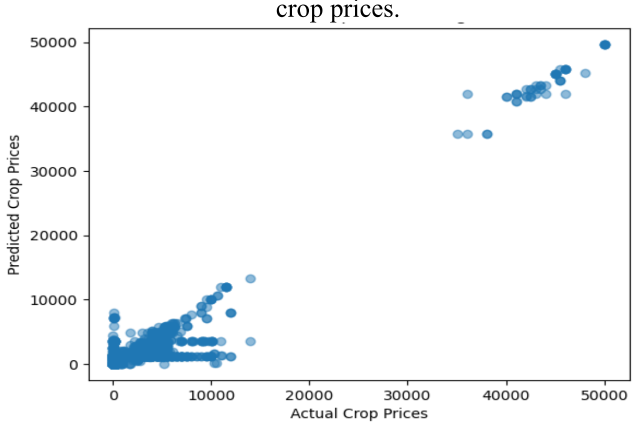

Fig.10. Decision Tree performance for Predicted and Actual crop prices.

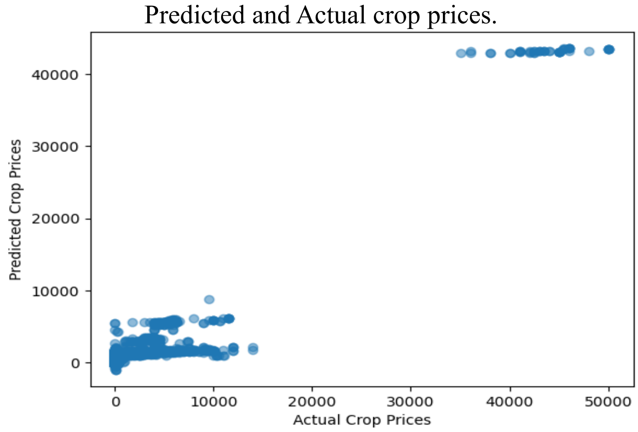

Fig.11. Linear Regression performance for Predicted and Actual crop prices.

By comparing the values of real prices to expected prices, all four algorithms are put to the test. Random forest regression has 93.059% accuracy, Decision tree regression is second with 92.5060% accuracy, Gradient boosting regression has 91.944% accuracy, and linear regression has 90.77247% accuracy because it has more outliers when all four algorithms are compared. This shows that Random Forest Regressor performs better in terms of accuracy.

The result can not only be determined using a single factor, it is important to take the time of execution, MAE, and RMSE into account to figure out the best algorithm. Below Figure.12 shows the accuracy comparison, Figure.13 shows the Execution time comparison, and Table.4 displays the performance comparison.

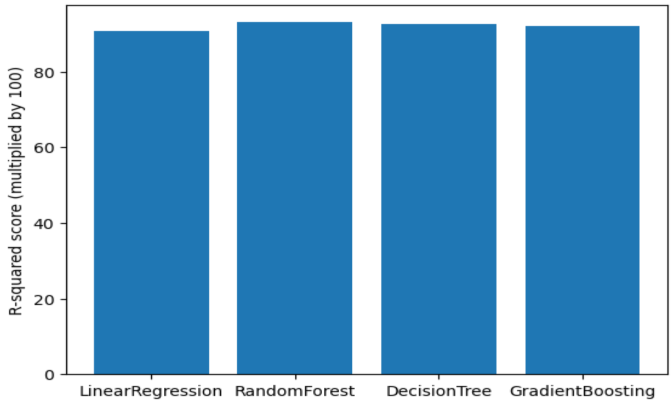

Fig.12. Comparing Accuracy

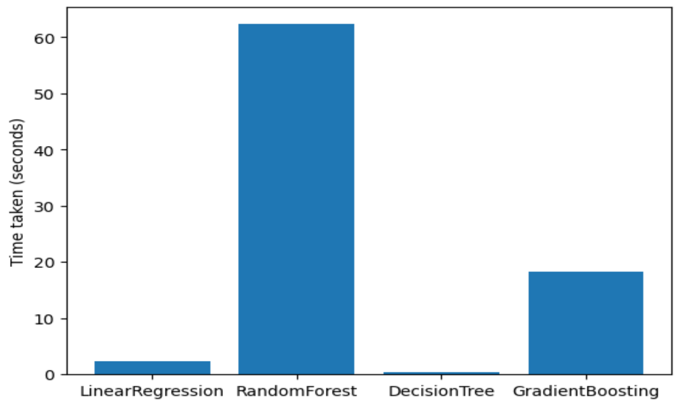

Fig.13. Comparing Execution time

Table.4. Performance comparison

Regression Model	MAE	RMSE	R_2-Score	Execution Time in seconds
Random Forest	0.261	0.117	0.9309	60
Decision Tree	**0.275**	**0.135**	**0.925**	**1**
Linear Regression	0.359	0.172	0.9077	3
Gradient Boosting	0.311	0.163	0.91944	18

When comparing the four algorithms for predicting crop prices, it is already determined that random forest has greater accuracy than the other models. However, when considering the Time factor, MAE, and RMSE, Random forest regression requires more time for prediction than all other consequences. But the Decision tree performs well with the 0.275 as MAE value, 0.135 as the RMSE value, R2 Score of 0.925, and the time taken for the execution is also low, which concludes utilizing the Decision tree regression for crop price prediction is better because it performs similarly to a Random forest regressor in terms of accuracy and also has a lower prediction time requirement with fewer errors.

Machine Rental Price Prediction:

The four different algorithms are used for machine rental price prediction same as in crop price prediction. Below graphs display the performance results.

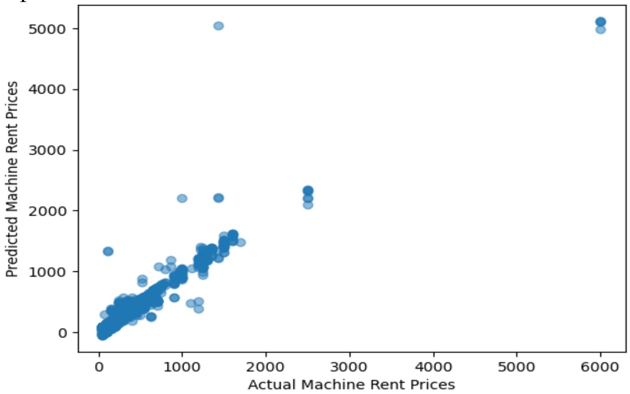

Fig.14. Linear Regression performance for Predicted and Actual Machine rental prices.

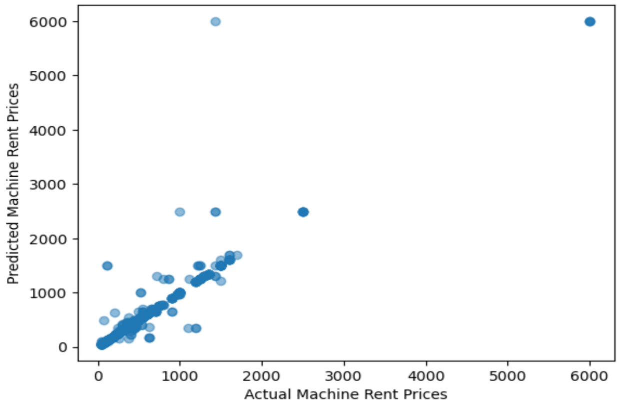

Fig.15. Decision Tree performance for Predicted and Actual Machine rental prices.

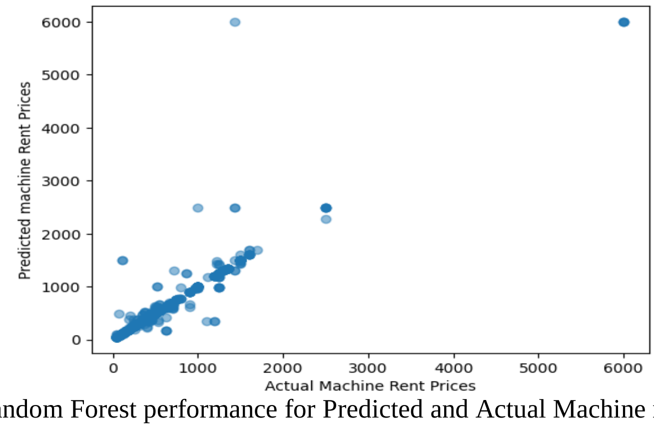

Fig.16. Random Forest performance for Predicted and Actual Machine rental prices.

The four algorithms are also tested here by comparing the values of real prices to predicted prices, as indicated in the crop price prediction section. In a comparison of the four algorithms, linear regression has an 89.89362% accuracy rate, followed by decision tree regression with an 88.4256% accuracy rate, and random forest regression with an 88.4191% accuracy rate.

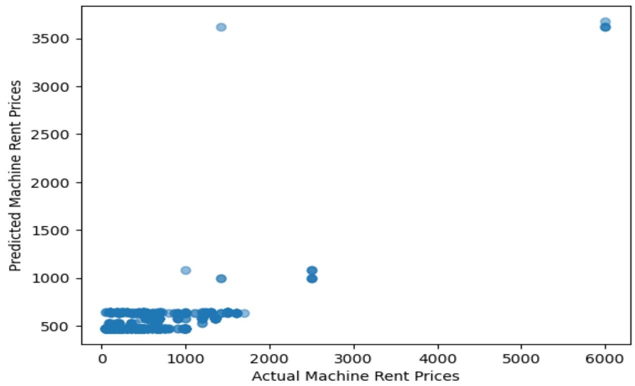

Fig.17. Gradient Boosting performance for Predicted and Actual Machine rental prices.

The accuracy of the gradient boosting regressor is 43.39467% because it has more outliers. It is concluded that Linear regression provides greater results and accuracy by comparing the other four models.

Below Figure.18 shows the accuracy comparison, Figure.19 shows the Execution time comparison, and Table.5 displays the performance comparison for machine rental prices.

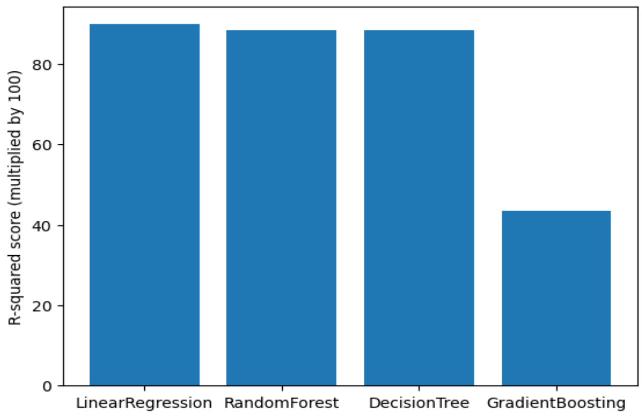

Fig.18. Comparing Accuracy

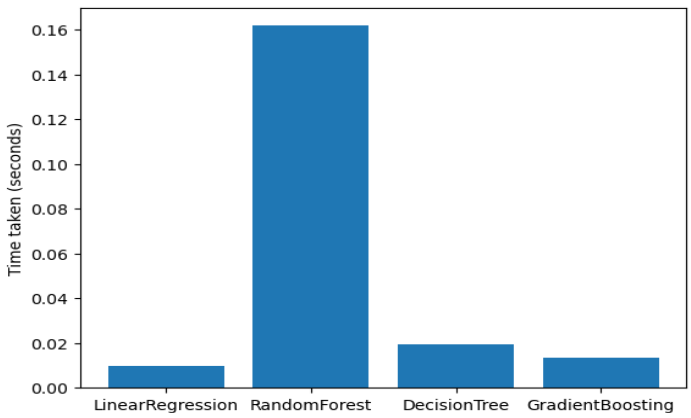

Fig.19. Comparing Execution Time

Table.5. Performance comparison

Regression Model	**MAE**	**RMSE**	**R_2-Score**	**Execution Time in seconds**
Decision Tree	0.375	0.327	0.8842	0.02
Random Forest	0.379	0.321	0.88419	0.16
Linear Regression	**0.256**	**0.301**	**0.8989**	**0.01**
Gradient Boosting	0.741	0.764	0.4339	0.015

It has already been determined that Linear regression has higher accuracy in machinery rental price prediction when compared to the other four algorithms, but when execution time, MAE, and RMSE are taken into account, it has 0.256 as MAE value, 0.301 as RMSE value, 0.8989 as R2 score, and the time taken for execution is lower than all other models. Concludes that it is efficient to use Linear regression for machine rental price prediction.

V. CONCLUSION

Four different machine-learning algorithms were used to evaluate the system. The performance computation of the regression models exposed that Decision Tree performs better for Crop price while Linear Regression performs better for Machinery rental price than the other regression models considered in this study. In conclusion, our suggested approach analyses null values and noisy points first, then predicts the crop price by computing the minimum price and maximum price of the crop's attributes. We will consider factors like state, district, fuel type, and hourly rent when predicting machine rental prices. In comparison to the current method, the suggested system has several benefits, including flexibility, efficiency, accuracy, user-friendliness, and integration with other agricultural systems.

The suggested system has tools for estimating agricultural crop prices and equipment rental costs, which can benefit the agricultural sector. To improve the system's capabilities and expand it to new markets and geographical areas, more research can be done. By utilizing all of these algorithms, we have concluded that these approaches require less time to learn the crop and machinery rent costs as well as the pricing of other states in both models. However, the current method might not be accurate or dependable for these approaches. These methods address several issues, including the unpredictability of commodity price swings and the lack of agricultural equipment. The main issue that farmers confront is estimating the precise price of products and machinery, and this proposed approach meets that need.

REFERENCES:

[1] Bayona-Oré, Sussy, Rino Cerna and E. T. Hinojoza, "Machine learning for price prediction for agricultural products", WSEAS Transactions on Business and Economics, Vol. 18, E-ISSN. 2224-2899, 2021.

[2] S. Singh, "Institutional Innovations in the Delivery of Farm Services in India", Springer, pp. 33-70, 2018.

[3] Khodabakhshian Rasool and Mohsen Shakeri, "Prediction of repair and maintenance costs of farm tractors by using of preventive maintenance", International Journal of Agriculture Sciences, Vol. 3, No. 1, pp. 39-44, 2011.

[4] T. Yezekyan, Marco Benetti, Giannantonio Armentano, Samuele Trestini, Luigi Sartori and F. Marinello, "Definition of reference models for power, mass, working width, and price for tillage implements", Agriculture, Vol. 11, No. 3, pp. 197, 2021.

[5] M. T. Shakoor, Karishma Rahman, Sumaiya Nasrin Rayta and Amitabha Chakrabarty, "Agricultural production output prediction using Supervised Machine Learning techniques", in Proceedings of 1st International Conference on Next Generation Computing Applications (NextComp), Mauritius, pp. 182-187, 2017.

[6] S. Pandit, B. Sahithi, T. Saheli, D. Ramanika and N. Anil Kumar, "Crop price prediction system using machine learning algorithms", Quest Journals Journal of Software Engineering and Simulation, Vol. 06, No. 01, pp. 14-20, 2020.

[7] Rakhra Manik, Priyansh Soniya, Dishant Tanwar, Piyush Singh, Dorothy Bordoloi, Prerit Agarwal, Sakshi Takkar, Kapil Jairath and Neha Verma, "Crop price prediction Using random forest and decision tree regression: A review", Materials Today: Proceedings, In Press, 2021.

[8] Ranganatha S and Y P Gowramma, "Eigen and HOG Features based Algorithm for Human Face Tracking in Different Background Challenging Video Sequences", International Journal of Image, Graphics and Signal Processing (IJIGSP), Vol.14, No.4, pp. 70-83, 2022. doi: 10.5815/ijigsp.2022.04.06

[9] Neeraj Soni and Jagruti Raut, "Crop price prediction using machine learning techniques", International Advanced Research Journal in Science, Engineering and Technology, Vol. 9, Issue. 5, 2022.

[10] Ranjani Dhanapal, A. AjanRaj, S. Balavinayagapragathish and J. Balaji, "Crop price prediction using supervised machine learning algorithms", In Proceedings of International Conference on Computing, Communication, Electrical and Biomedical Systems (ICCCEBS), Journal of Physics: Conference Series, Vol. 1916, No. 1, 2021.

[11] Madhuri Shripathi Rao, Arushi Singh, N.V. Subba Reddy and Dinesh U. Acharya, "Crop prediction using machine learning", In Proceedings of 1st International Conference on Artificial Intelligence, Computational Electronics and Communication System (AICECS 2021), Journal of Physics: Conference Series, vol. 2161, No. 1, pp. 012033, 2022.

[12] Ishita Ghutake, Ritesh Verma, Rohit Chaudhari and Vidhate Amarsinh, "An intelligent crop price prediction using suitable machine learning algorithm", In Proceedings of International Conference on Automation, Computing and Communication (ICACC), ITM web of conferences, Vol. 40, pp. 03040, 2021.

[13] G. S. Kakaraparthi and S. Prabhakar Rao, "Crop price prediction using machine learning", International Research Journal of Modernization in Engineering Technology and Science, Vol. 3, Issue. 6, 2021.

[14] R. Rohith and R. Vishnu, "Crop Price Prediction and Forecasting System using Supervised Machine Learning Algorithms", International Journal of Advanced Research in Computer and Communication Engineering, Vol. 9, Issue. 3, 2020.

[15] S. Vijayasree, "Prediction of crop yield in precision agriculture using machine learning", ICTACT Journal on Data Science and Machine Learning, Vol. 2, Issue. 4, pp. 241-244, September 2021.

[16] R Chandana, Ranganatha S and Sanjay, "Detection of a Facemask Using Convolution Neural Network", in Proc. of IEEE International Conference on Data Science and Information System (ICDSIS), pp.1-5, July 2022.

[17] R. Bhavani and Ajoe Thambi, "Managing irrigation needs based on smart decisions using machine learning", ICTACT Journal on Soft Computing, Vol. 12, Issue. 2, pp. 2540-2544, 2020.

[18] Shivashankara S and Ranganatha S, "Real-Time ASL Single Handed Video Gestures Recognition: A Deep Neural Network Approach", International Journal of Special Education, Vol.37, Issue.3, pp.11055-11068, 2022.

[19] Sabu and K. M. Kumar, "Predictive analytics in Agriculture: Forecasting prices of Arecanuts in Kerala", In Proceedings of Third International Conference on Computing and Network Communications (C0C0Net'1), Elsevier, Vol. 171, pp. 699-708, 2020.

[20] Zhang, D., Chen, S., Liwen, L. and Xia, Q., "Forecasting agricultural commodity prices using model selection framework with time series features and forecast horizons", IEEE Access, Vol. 8, pp. 28197–28209, 2020.

[21] Yung-HsinPeng, Chin-Shun Hsu and Po-Chuang Huang, "Developing Crop Price Forecasting Service Using Open Data from Taiwan Markets", In Proceedings of IEEE Conference on Technologies and Application of Artificial Intelligence (TAAI), pp. 172-175, 2015.

[22] Wu, H., Zhu, M., Chen, W. and Chen, "A new method of large-scale short-term forecasting of agricultural commodity prices: Illustrated by the case of agricultural markets in Beijing", Journal of Big Data, Vol. 4, No. 1, pp. 1-22, 2017.

[23] https://www.kaggle.com