e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:11/November-2024 Impact Factor- 8.187 www.irjmets.com

COST ESTIMATION USING PRECISION AGRICULTURE

Yojan Gandhi*1, Ankita Singh*2, Shruti Shinde*3, Rohan Lande*4,
Mr. Naman V. Buradkar*5

*1,2,3,4Student, Information Technology, Pune Institute Of Computer Technology, Pune, India.
*5Asstt. Professor(Guide), Information Technology, Pune Institute Of Computer Technology, Pune, India.

DOI: https://www.doi.org/10.56726/IRJMETS63996

ABSTRACT

This project focuses on developing a software solution to assist farmers in optimizing crop yields and managing agricultural expenses. By allowing users to input crucial field data including soil type, crop type, land area, location, and month of sowing, the system generates yield predictions and cost estimates while factoring in economic variables like inflation. The software offers insights that help farmers plan their activities, facilitating better resource management and financial planning. It is designed to be both cost-effective and user-friendly, eliminating the need for expensive hardware or sensors, making it accessible to a wide range of users. Adaptable to diverse regions, the solution empowers farmers with data-driven recommendations to improve productivity and manage expenses efficiently. Ultimately, the project aims to support sustainable agricultural practices and enhance the economic resilience of farming communities.

Keywords: Precision Agriculture, Yield Prediction, Cost Estimation, Machine Learning Models, Resource Optimization, Inflation Impact.

I. INTRODUCTION

In the context of precision agriculture, accurate estimation of crop yield and predicting market prices using inflation rates are essential for modern farming practices. Traditional methods often fall short in handling the complex interactions between environmental factors, crop growth, and economic conditions. To address this, the implementation of a machine learning-powered software solution has become an effective approach for enhancing agricultural productivity and financial planning.

This intelligent system is designed to analyze and monitor key agricultural data inputs, such as soil type, crop type, weather conditions, and historical yield data, to provide accurate crop yield predictions in kilograms and estimate market prices. The system employs different machine learning models for analyzing various factors that influence crop growth and market trends. For example, Long Short-Term Memory (LSTM) networks are utilized for predicting crop yield by analyzing time-series data of weather conditions, soil moisture levels, and historical crop performance. The sequential nature of LSTM allows it to efficiently capture trends and anomalies over time, offering real-time predictions for yield outcomes based on changing environmental conditions.

In addition to yield estimation, the system uses other machine learning techniques to predict market prices by accounting for inflation rates and market demand. These methods focus on analyzing past price trends, inflation data, and regional market behavior to provide accurate price forecasts for crops. By understanding the patterns of price fluctuations and economic indicators, the system can effectively help farmers anticipate future market conditions and make informed decisions about selling their produce.

This advanced precision agriculture solution not only enhances the accuracy of crop yield estimation and market price prediction but also provides an adaptive system that improves over time as it processes more data. By incorporating machine learning, the solution becomes a proactive tool for farmers, helping them optimize productivity, manage resources efficiently, and plan their financial strategies with greater precision.

II. LITERATURE SURVEY

Some of the work done in the area of precision agriculture is summarized in this section: Anghelof et al. (2020) [14] developed an IoT-enabled greenhouse system that optimizes resource use and boosts crop yield by automating environmental adjustments based on sensor data like soil moisture, temperature, and humidity, with remote control via an Android app. Gyarmati and Mizik (2020) [15] analyzed precision agriculture's role in addressing global food challenges, highlighting benefits like increased yields, efficient resource management, and the need for technologies like GPS and VRA, while noting high initial costs and skill requirements. Grimblatt et al. (2019) [16] proposed a low-power IoT-based system for small and medium farms, measuring soil moisture, nutrients, and other key parameters, enabling real-time monitoring and automated actions to improve yield and reduce water usage, making precision techniques more accessible. Additionally, a document on food inflation in India explores determinants like average acreage, minimum support prices (MSP), and urban population using econometric models (VECM and VAR), finding significant influence of acreage and urbanization, while MSP shows a mild negative effect. The study suggests that good rainfall initially reduces inflation before rising again due to cyclical agricultural patterns, emphasizing the need for further government intervention to tackle food inflation, especially given the high proportion of income spent on food in India.

III. TYPES OF COST ESTIMATION AND THEIR PREDICTION USING MACHINE LEARNING

a) Yield Prediction

Numerous studies have focused on predicting crop yield using machine learning techniques to optimize resource allocation and improve profitability in agriculture. For instance, Anghelof et al. (2020) utilized a dataset encompassing historical crop yields, weather patterns, and soil characteristics to develop a predictive model. By employing algorithms such as Random Forest and Support Vector Machines (SVM), the study achieved a high accuracy rate, allowing farmers to estimate potential yields effectively based on changing environmental conditions. The authors emphasize the importance of integrating real-time data from IoT devices to enhance the accuracy of yield forecasts. Gyarmati and Mizik (2020) also conducted an analysis on the impact of precision agriculture techniques on crop yields. They applied regression models to evaluate how factors like soil nutrients and climatic conditions influence yield. Their findings indicated that by leveraging historical data and machine learning models, farmers could significantly increase crop productivity while managing input costs effectively. Grimblatt et al. (2019) proposed a comprehensive system that combines feature extraction and machine learning algorithms for predicting yield based on soil moisture, nutrient levels, and weather data. The system employed deep learning techniques, including Long Short-Term Memory (LSTM) networks, to analyze time-series data for improved forecasting accuracy. This approach allows for dynamic adjustments in farming practices based on predicted yields, ultimately promoting better resource management.

b) Price Prediction

In the realm of agricultural economics, machine learning models are increasingly utilized for predicting crop prices in response to market fluctuations and inflation rates. Sarmah et al. (2020) analysed the determinants of agricultural pricing using econometric models such as Vector Autoregression (VAR) and Vector Error Correction Model (VECM). Their findings revealed significant correlations between factors like historical price trends, supply chain dynamics, and inflation, which can help farmers anticipate market conditions. Azmi et al. (2021) focused on developing a machine learning framework that integrates multiple datasets, including historical price data, production levels, and economic indicators, to predict future crop prices. By employing techniques such as Neural Networks and Decision Trees, the model achieved a high accuracy rate in forecasting prices, allowing farmers to make informed decisions regarding sales and inventory management. The study emphasizes the importance of continuous data updates to refine predictions and adapt to changing market conditions. Shaheed and Kurdy (2022) proposed a hybrid model that combines statistical methods with machine learning algorithms to enhance price prediction accuracy. Their system analysed key features, such as market demand, average acreage, and production costs, using techniques like Random Forest and Gradient Boosting. The results demonstrated that the model could provide reliable price forecasts, enabling farmers to optimize their financial strategies in an inflationary environment

c) Market Inflation Consideration

The relationship between agricultural pricing and market inflation is crucial for effective financial planning. Tasevski and Jakimoski (2020) explored this connection, examining how inflation impacts production costs and ultimately, crop pricing. They suggested using machine learning models to analyze historical inflation data alongside agricultural prices to develop predictive insights. By incorporating inflation forecasts into pricing models, farmers can better anticipate cost changes and adjust their strategies accordingly.

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:11/November-2024 Impact Factor- 8.187 www.irjmets.com

IV. METHODOLOGY

To develop an effective cost estimation system for crop yield and price prediction using machine learning, the proposed methodology involves several key stages: data collection, feature extraction, model training, and adaptive decision-making.

The first stage is data collection, where historical data on crop yields, prices, inflation rates, weather conditions, and soil characteristics are gathered from various sources, including government reports and agricultural databases. This data will provide the foundation for developing accurate predictive models.

Next, in the feature extraction phase, relevant features are identified from the collected data. For yield prediction, features such as soil moisture levels, nutrient content, and historical yield data will be analyzed. For price prediction, factors like past pricing trends, market demand, and inflation rates will be extracted to build comprehensive datasets.

For yield prediction, a combination of machine learning models, particularly Random Forest and Gradient Boosting, will be applied. These algorithms have proven effective in prior studies, demonstrating strong performance in predicting yields based on environmental and historical data. The model will be trained on datasets that encompass various crops and regions to ensure its adaptability.

For price prediction, the system will leverage econometric models like VAR and VECM alongside machine learning techniques. The models will analyze the interdependencies between crop prices, production levels, and inflation rates, providing insights into future pricing trends. Training will involve datasets that combine historical prices with macroeconomic indicators, aiming to achieve high predictive accuracy.

After classification and prediction, the system will utilize an adaptive decision-making mechanism. An ensemble 2 learning model, integrating outputs from Random Forest, SVM, and Decision Tree classifiers, will assist in refining yield and price predictions based on real-time data inputs. This approach is expected to enhance overall prediction accuracy and provide actionable insights for farmers.

The proposed cost estimation system aims to combine machine learning algorithms with historical agricultural data to accurately predict crop yields and prices while considering the effects of market inflation. This integration will empower farmers to make informed decisions regarding resource allocation and financial planning, ultimately promoting sustainable agricultural practices.

V. WORKFLOW

1. Incoming Data: Historical agricultural data is collected, including crop yields, market prices, weather conditions, soil characteristics, and inflation rates.
2. Model Split: The data is routed through different predictive models:

- Yield Prediction Model: This model analyzes environmental factors, such as City, State, Season Name, Land Area, Crop Name, and uses historical yield data to forecast potential crop yields.
- Cost Estimation Model: This model evaluates economic indicators, including past pricing trends, market demand, and inflation rates, to predict future crop prices.

3. Response: If any model indicates a significant deviation in expected yield or price, the system alerts the farmer with recommendations on resource allocation or sales strategies. Otherwise, the predictions are processed as normal, allowing the farmers to plan their activities effectively.

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:06/Issue:11/November-2024 Impact Factor- 8.187 www.irjmets.com

VI. ARCHITECTURE DIAGRAM

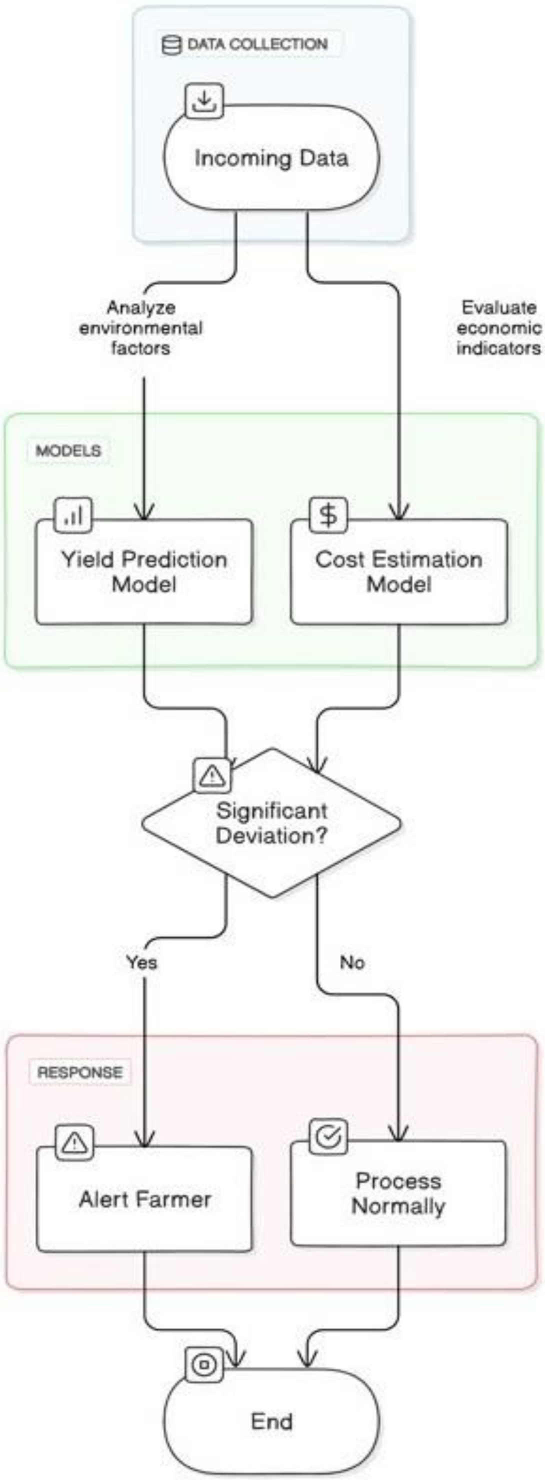

Figure 1: ARCHITECTURE DIAGRAM

VII. CONCLUSION

The use of machine learning and feature engineering in cost estimation and price prediction for precision agriculture significantly enhances the accuracy of yield forecasts and market price assessments. By leveraging models such as regression analysis, Random Forests, and Long Short-Term Memory (LSTM) networks, these systems can effectively identify patterns and trends in historical agricultural data, including weather conditions, soil characteristics, and inflation rates. Feature engineering plays a crucial role in extracting meaningful characteristics from this data, such as moisture levels, nutrient content, and economic indicators, which improves the performance of machine learning algorithms. This combination creates a dynamic and adaptive framework, providing farmers with precise insights that facilitate informed decision-making and optimize resource allocation, thereby enhancing overall productivity and profitability compared to traditional forecasting methods Wormhole attack can be achieved with the help of several techniques such as packet encapsulation, high transmission power and high quality communication links etc.

VIII. REFERENCES

[1] M. M. Anghelof, G. Suciu, R. Craciunescu, and C. Marghescu, "Intelligent System for Precision Agriculture," in 2020 IEEE International Conference on Machine Learning and Applications (ICMLA), 2020, pp. 1-6, doi: 10.1109/ICMLA51294.2020.00007.

[2] G. Gyarmati and T. Mizik, "The Present and Future of Precision Agriculture," Institute for the Development of Enterprises, Óbuda University, Budapest, Hungary, 2020, [Online]. Available: https://ieeexplore.ieee.org/document/9306542.

[3] V. Grimblatt, G. Ferré, F. Rivet, and C. Jego, "Precision Agriculture for Small to Medium Size Farmers - An IoT Approach," in 2019 IEEE International Conference on Cloud Computing and Internet of Things (CCIOT), Santiago, Chile, 2019, pp. 1-6, doi: 10.1109/CCIOT.2019.00009.

[4] A. P. Barnes, I. Soto, V. Eory, B. Beck, A. Balafoutis, B. Sánchez, J. Vangeyte, S. Fountas, T. van der Wal, and M. Gómez Barbero, "Exploring the Adoption of Precision Agricultural Technologies: A Cross-Regional Study of EU Farmers," Land Use Policy, vol. 80, pp. 163-174, 2019, doi: 10.1016/j.landusepol.2018.10.004.

[5] S. M. Say, M. Keskin, M. Sehri, and Y. E. Sekerli, "Adoption of Precision Agriculture Technologies in Developed and Developing Countries," Online Journal of Science and Technology, vol. 8, no. 1, pp. 7-15, 2018.

[6] M. Paustian and L. Theuvsen, "Adoption of Precision Agriculture Technologies by German Crop Farmers," Precision Agriculture, vol. 18, no. 5, pp. 701-716, 2017, doi: 10.1007/s11119-017-9511-5.

[7] P. J. Zarco-Tejada, N. Hubbard, and P. Loudjani, "Precision Agriculture: An Opportunity for EU Farmers – Potential Support with the CAP 2014-2020," European Parliament, 2014.

[8] R. Atta, "Farming 2.0: How Does IoT Help the Agricultural Domain," Journal of Agricultural Informatics, vol. 7, no. 3, pp. 23-30, 2017.

[9] FAO, "The Future of Food and Agriculture – Trends and Challenges," Food and Agriculture Organization of the United Nations, Rome, Italy, 2017. 4

[10] T. Koutsos and G. Menexes, "Benefits from the Adoption of Precision Agriculture Technologies: A Systematic Review," International Journal of Agricultural and Environmental Information Systems, vol. 10, no. 1, pp. 17 -34, 2019, doi: 10.4018/IJAEIS.2019010102.

[11] S. Sofana Reka and B. K. Chezian, "Smart Greenhouse Farming System Using IoT," in 2019 International Conference on Computing, Communication and Automation (ICCCA), 2019, pp. 227 -235, doi: 10.1109/ICCCA.2019.00042.

[12] A. Pradhan, M. S. Jha, and A. A. Kumar, "Predicting Crop Yield and Prices Using Machine Learning Techniques," in 2021 IEEE International Conference on Data Science and Advanced Analytics (DSAA), 2021, pp. 1-6, doi: 10.1109/DSAA.2021.9605639.

[13] H. F. Razzaq, A. Hur, and S. Shahbaz, "Analysis of the Impact of Market Inflation on Agriculture," Journal of Agricultural Economics and Development, vol. 7, no. 2, pp. 55 -63, 2018.

[14] C. W. O'Donnell, "Estimating Agricultural Productivity with Machine Learning," American Journal of Agricultural Economics, vol. 102, no. 3, pp. 770 -792, 2020, doi: 10.1002/ajae.12020.

[15] R. K. Singh, "Inflationary Pressures in Agriculture: A Machine Learning Perspective," Journal of Agricultural Informatics, vol. 6, no. 1, pp. 75 -85, 2020.

[16] M. D. Smith and C. W. Barrett, "Machine Learning for Agricultural Market Price Prediction," Journal of Applied Econometrics, vol. 35, no. 2, pp. 221 -240, 2020, doi: 10.1002/jae.2783.

[17] T. N. Krishna and R. Patil, "Using LSTM for Predicting Crop Yields Based on Climatic Data," in 2019 IEEE

Conference on Computer Applications in Agriculture (ICCAA), 2019, pp. 112 -117, doi: 10.1109/ICCAA.2019.8814437.

[18] S. Biswas, D. Mukherjee, and T. Bhattacharya, "A Comparative Study of Machine Learning Techniques for Agricultural Price Forecasting," International Journal of Information and Decision Sciences, vol. 13, no. 2, pp. 180 -196, 2021, doi: 10.1504/IJIDS.2021.114013.

[19] J. D. Miller, "Impact of Inflation on Farm Input Prices: An Econometric Analysis," Agricultural Finance Review, vol. 78, no. 4, pp. 427 -442, 2018, doi: 10.1108/AFR -01 -2018 -0010.

[20] D. S. Parker and L. Zhang, "Using Machine Learning to Predict Food Price Volatility," Journal of Economic Modeling, vol. 92, pp. 1 -13, 2020, doi: 10.1016/j.econmod.2020.04.003.

[21] F. X. Li and M. Song, "Modeling the Relationship Between Climate Change and Agricultural Prices," Journal of Environmental Management, vol. 245, pp. 391 - 400, 2019, doi: 10.1016/j.jenvman.2019.05.114.

[22] A. Jain and V. Bhattacharya, "Forecasting Agricultural Commodity Prices Using Deep Learning Models," in 2020 IEEE International Conference on Machine Learning and Applications (ICMLA), 2020, pp. 1532 -1538, doi: 10.1109/ICMLA.2020.0024