LITERATURE REVIEW ON RECOMMENDER SYSTEM FOR CROP PREDICTION THROUGH COLLABORATIVE FILTERING USING MACHINE LEARNING

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ABSTRACT

An extensive investigation of the use of machine learning (ML) techniques in crop prediction is presented in this research study. Given the problems posed by climate change and the growing worldwide need for food, machine learning (ML) presents a possible path for improving agricultural output estimates. The study examines the approaches, resources, difficulties, and possible uses of machine learning in the context of agricultural forecasting.

KEYWORDS

Machine Learning, Crop Prediction

1. INTRODUCTION

In recent years, agriculture has undergone a significant transformation, leveraging advancements in technology to enhance productivity, sustainability, and efficiency. The use of machine learning algorithms for crop prediction is one such technical advancement that has gained popularity. Machine learning algorithms allow farmers and other agricultural users to make well-informed decisions, allocate resources optimally, and reduce risks related to crop production by utilizing large volumes of agricultural data.

Crop prediction involves forecasting key parameters such as yield, disease susceptibility, and optimal planting times, among others, based on various environmental factors, historical data, and agronomic practices. Traditional methods of crop prediction often relied on manual observation, experience, and limited datasets, leading to inefficiencies and inaccuracies. But a new age of data-driven decision-making in agriculture has begun with the development of machine learning tools.

Machine learning algorithms offer several advantages in crop prediction. To find intricate patterns and linkages, they can examine vast amounts of multidimensional data, such as soil composition, weather patterns, satellite images, and past crop performance. Farmers may maximize inputs like water, fertilizer, and pesticides while limiting their impact on the environment by using machine learning algorithms that produce precise predictions and insights into crop behavior based on the training of models on this broad dataset.

Moreover, machine learning facilitates real-time monitoring and adaptive management strategies, allowing farmers to respond swiftly to changing conditions and emerging threats. For example, predictive models can alert farmers to potential disease outbreaks or adverse weather events, enabling timely interventions to mitigate losses and maximize yields. Additionally, by integrating data from IoT sensors, drones, and other smart agriculture technologies, machine learning algorithms can provide granular insights at the field level, empowering farmers to implement precision agriculture practices tailored to specific crop requirements.

Even with machine learning's potential for crop prediction, several issues still need to be resolved, such as scalability, model interpretability, and accessible and high-quality data. To promote the responsible and fair implementation of machine learning technologies in agriculture, stakeholders such as researchers, policymakers, technology providers, and farmers must work together to address these difficulties.

In summary, machine learning algorithms for crop prediction have the potential to completely transform agriculture by facilitating data-driven decision-making, maximizing resource use, and boosting resilience to market and environmental uncertainty. Farmers may create new avenues for lucrative and sustainable agricultural production and guarantee food security for future generations by utilizing artificial intelligence.

2. PROBLEM STATEMENT

2.1. THE NEED FOR CROP PREDICTION:

- Farmers and agricultural experts require accurate and timely information on crop yield predictions to make informed decisions.
- Traditional methods of crop yield prediction may lack accuracy and may not consider various influential factors.

2.2. LEVERAGING RECOMMENDER SYSTEMS:

- Recommender systems have proven effective in various domains for providing personalized recommendations.
- Applying recommender systems to crop yield prediction can provide valuable insights to farmers and help optimize their agricultural practices.

2.3.UTILIZING COLLABORATIVE FILTERING:

- Collaborative filtering is a machine learning technique that leverages user preferences and similarities to make predictions.
- Applying collaborative filtering to crop yield prediction can help identify patterns and similarities among different farms, leading to more accurate predictions.

2.4. CHALLENGES AND POTENTIAL ISSUES:

- Limited availability of historical data: Obtaining a comprehensive dataset on crop yield, weather conditions, soil quality, and farming practices may be challenging.
- Data quality and reliability: Producing trustworthy forecasts requires guaranteeing the precision and dependability of the gathered data.
- Scalability: Developing a scalable system that can handle a large number of users and farms while maintaining efficiency and accuracy.
- Interpretability: Ensuring that the recommendations provided by the system are understandable and transparent to the end-users.

2.5. PROPOSED SOLUTION:

- Using collaborative filtering and machine learning methods to create a recommender system for crop prediction in a practical manner
- Gathering and preparing pertinent data, such as past crop statistics, meteorological information, soil quality, and agricultural techniques.

- Creating a scalable and precise machine learning model that can produce customized crop forecasts using cooperative filtering methods.
- Giving farmers advice that is easy to understand and use, so they can optimize their farming operations and make data-driven decisions.
- By tackling these issues and putting the suggested solution into practice, we can provide farmers with a useful tool that will help them plan their agricultural operations more effectively and anticipate crops with more accuracy.

3. SIGNIFICANCE

The significance of the study on crop prediction using machine learning algorithms lies in its potential to revolutionize agricultural practices. By leveraging advanced technology and data-driven approaches, the study aims to:

- Enhance Agricultural Productivity: Improved crop prediction accuracy can help farmers optimize resource allocation, mitigate risks, and maximize yields, contributing to increased agricultural productivity.
- Ensure Food Security: Accurate crop prediction facilitates better planning and management of food production, helping to ensure stable food supplies and mitigate the impact of food shortages or price fluctuations.
- Foster Sustainability: Machine learning-based crop prediction can encourage sustainable agricultural practices and lessen environmental impact by enabling more accurate and efficient use of resources like water, fertilizer, and pesticides.
- Empower Farmers: Accessible and reliable crop prediction tools empower farmers with timely insights and actionable information, enabling them to make informed decisions and adapt to changing environmental and market conditions.
- Drive Innovation: Research in this area drives innovation in machine learning techniques, data integration methods, and agricultural technologies, paving the way for continuous improvement in crop prediction accuracy and effectiveness.
- Overall, the study holds the potential to improve agricultural outcomes significantly, contribute to global food security, and drive sustainable development in rural communities.

4. LITERATURE REVIEW

Kavita Jhajharia and Pratistha Mathur [1]focused on utilizing machine learning techniques to create an agricultural yield forecast model for the Rajasthan area of India. For farmers and policymakers to make educated decisions about agricultural practices, resource allocation, and food security, the authors recognize the significance of precise crop output forecasts. Support vector regression (SVR), random forest (RF), artificial neural networks (ANN), and other machine learning techniques are used in the study to examine historical data on agricultural yields, weather patterns, soil conditions, and other pertinent variables. Using the data at hand, these algorithms are utilized to create prediction models that project crop yields. The authors emphasized how important feature selection and data pretreatment methods are to raise the prediction models' accuracy [1].

Dongyang Huo, etal. [2]emphasized the several difficulties faced by farmers, including the need for more food production, water shortages, and climate change. They contend that one important factor in resolving these issues might be smart farming, which makes use of data-driven infrastructure. Numerous facets of smart farming were thoroughly examined in the research. It investigates how real-time data on weather, soil moisture, and crop health might be collected in agriculture through the use of Internet of Things (IoT) devices like sensors and drones. The writers emphasized the value of using machine learning and data analytics methods to interpret this information and provide farmers with useful insights [2].

Ravi Ray Chaudhari, et al. [3] began by talking about the drawbacks of conventional agricultural practices, including poor resource management, erratic weather, and little control over crop development. The authors suggest a hybrid architecture that combines IoT devices and machine learning algorithms to allow precise farming as a solution to these problems. The authors go into great depth on the suggested structure, emphasizing its main features and elements. They highlight how machine learning (ML) algorithms are used to analyze data from Internet of Things (IoT) devices including drones, weather sensors, and soil moisture sensors. The framework can offer precise insights and forecasts about crop health, soil conditions, and the best way to allocate resources by utilizing machine learning techniques. The study also offers a thorough examination of the advantages and drawbacks of the hybrid framework [3].

Alexandros Oikonomidisa, et al. [4]centered on carrying out an organized study of the literature to investigate the usage of deep learning methods in crop production forecasting. The authors acknowledge that deep learning algorithms can extract intricate patterns and correlations from agricultural data, which might result in more precise crop output estimates. The paper thoroughly examines a variety of studies and research publications that have applied deep learning techniques to the prediction of agricultural output. To evaluate the efficacy of deep learning methods in this situation, it looks at the approaches, datasets, and performance measures employed in these works. The authors describe the many deep learning architectures used, such as deep belief networks (DBNs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs) [4].

Martin Kuradusenge, etal. [5]employed machine learning algorithms to predict agricultural harvests based on meteorological data and provide information about production patterns. Crop yields for maize and potatoes in Ireland, together with meteorological information, were gathered from various sources. The data were analyzed using three distinct regression models: Random Forest, Polynomial Regression, and Support Vector Regressor. Precipitation and temperature were used as indicators. The models were trained and tested. The results indicate that Random Forest is the best model, with root mean square errors of 510.8 and 129.9 for potatoes and maize, respectively, and R2 values of 0.875 and 0.817 for the same crop datasets. The best weather conditions were identified for each crop to maximize crop productivity. According to the findings, the Random Forest model is advised for early crop yield prediction [5].

S Iniyan, et al. [6] emphasized the need for precise crop yield estimates for efficient planning and decision-making in agriculture. They talk about the drawbacks of conventional agricultural yield estimating techniques, namely their reliance on human data gathering and their poor accuracy. The study then explores the many data analytics methods applied to agricultural production prediction. examined the use of statistical models, machine learning algorithms, data from remote sensing, and other data-driven methodologies. The writers assess the benefits and drawbacks of each strategy, including information on how well it works and where it might be applied in various agricultural settings. The role of data sources in agricultural yield estimation was also covered in the article. It highlights how crucial it is to combine many data sets, including soil, weather, and historical yield data, to increase prediction accuracy [6].

Trapti Mishra and Pramod S. Nair [7]centered on developing machine learning-based forecasting models for farming suitability. The authors acknowledge the significance of precise agricultural forecasts in enhancing farming methods, allocating resources, and maintaining sustainable land management. The study analyzes soil and environmental data to forecast if a piece of land is suitable for a certain crop by using a variety of machine learning methods, such as support vector machines, random forests, and decision trees. Using the data at hand, these algorithms are used to create prediction models that can determine which crops are most suited for a certain location or area. The writers talk about how important feature selection and data pretreatment are to raising the prediction models' accuracy. To improve the accuracy of predictions, they stress the significance of choosing pertinent attributes and cleansing the data [7].

Dhruvi Gosai, et al. [8] presented a framework for analyzing and interpreting data from various sources using machine learning methods. They describe the procedures followed for gathering and preparing the data, including feature engineering and data cleaning methods. Predictive models are constructed using a variety of machine learning methods, including decision trees, support vector machines, and neural networks. The assessment procedure used to gauge the crop recommendation system's effectiveness was also included in the study. The algorithms' efficacy in generating precise crop recommendations is evaluated using metrics including accuracy, precision, and recall. The outcomes showed that, given the input parameters, the system could suggest appropriate crops [8].

Thomas van Klompenburg, et.al [9]began by stressing how crucial precise crop production forecasting is to agriculture's ability to manage resources and make wise decisions. It draws attention to how machine learning has the potential to be an effective tool for sifting through massive amounts of data, and finding patterns and links that allow for the creation of precise predictions. The authors identified and analyzed a broad variety of papers that focus on agricultural production prediction using machine learning algorithms after conducting a systematic evaluation of pertinent literature. They talked about the many methods and strategies used in these investigations, such as neural networks, support vector machines, decision trees, and regression models. The assessment also looks at the datasets that were utilized in the research, including historical yield data, crop management techniques, soil properties, and meteorological data. The authors discussed the evaluation metrics employed, such as root mean square error (RMSE) and mean absolute error (MAE), to assess the predictive capabilities of the models [9].

Pallavi Kamath, et.al[10] began by emphasizing the need for precise crop output projections for efficient agricultural planning, resource distribution, and decision-making. To find patterns and associations that might help with crop production prediction, it highlights the potential of data mining as an effective tool for studying big and complicated information. In addition to other variables including weather patterns, soil properties, and crop management strategies, the authors presented a methodology that makes use of data mining tools to examine historical crop production data. The preparation processes that are necessary to guarantee the quality and relevance of the data for the analysis were deliberated. Several data mining methods, including support vector machines, random forests, and decision trees, that are used in the agricultural production forecasting model were examined in this article. The authors discussed the metrics used to assess the accuracy and reliability of the predictions, such as mean absolute error (MAE) and root mean square error (RMSE) [10].

Mayank Champaneri, etal. [11] began by going over the significance of crop selection and the difficulties farmers have in coming to the best judgments. After that, the idea of machine learning is presented along with how it may be used to solve these problems. The authors suggested a framework for analyzing and interpreting data from many sources, such as weather patterns, soil properties, and agricultural production data, by using machine learning techniques. The approach for data collection and preprocessing, including feature engineering and data cleaning procedures, was described in the study article. Predictive models are constructed using a variety of machine learning methods, including decision trees, support vector machines, and neural networks. To precisely forecast how various crops would perform under particular circumstances, the models are trained using past data. The results showed that the proposed system performs well in recommending suitable crops based on the input parameters [11].

Sivanandhini P and Prakash J[12] begun by emphasizing the need of precise crop yield forecasts in farming methods. Next, it presented feed-forward and recurrent artificial neural networks as effective machine learning models for agricultural yield prediction. It was discovered that these models could recognize intricate links and patterns from past data, which allowed them to provide precise forecasts. The methods utilized to gather and preprocess the data, taking into account elements like crop management techniques, soil characteristics, and meteorological conditions, was explained by the writers. To provide an acceptable input dataset for the neural network models, a variety of characteristics are retrieved and modified. The study provided insights into the structure and optimization methods of the model by examining the architecture and training procedure of both feed-forward and recurrent neural networks. Metrics such as root mean square error (RMSE) and mean absolute error (MAE) are used to measure the accuracy of the predictions. The results demonstrated that both the feed-forward and recurrent neural networks perform well in predicting crop yields, with the latter showing superior performance in capturing temporal dependencies [12].

Saeed Khakhi, et al.[13] suggested a framework for extracting pertinent characteristics from satellite photos by using CNNs to detect spatial patterns. RNNs, which are intended to capture temporal dependencies in the data, such as weather patterns and crop development phases, are then given these characteristics. The author talked about the CNN-RNN framework's design and training procedure, highlighting how the two neural network models are integrated to use both temporal and geographical data for crop yield prediction. The author used actual agricultural yield datasets in tests to assess the framework's performance. The outcomes showed that, in terms of prediction accuracy, the CNN-RNN architecture performs better than solo CNN or RNN models and conventional machine-learning techniques [13].

Paras M. Khandelwal and Himanshu Chavhan [14]discussed about the importance of agriculture in the production of food worldwide and the necessity for creative ideas to raise agricultural productivity. It then went into the several AI methods and tools that may be used to address these issues. The authors stress the use of the Internet of Things (IoT) and remote sensing technologies in gathering real-time data for AI-driven agricultural systems. The study also discussed the difficulties and restrictions associated with applying AI to agriculture, such as the necessity for farmer-friendly interfaces, cost-effectiveness, and the availability and quality of data. It highlighted how crucial it is for agricultural specialists, computer scientists, and data analysts to work together collaboratively to create useful AI solutions that satisfy farmers' demands [14].

Toshichika Iizumi et.al [15] stressed on how crucial precise crop production forecasting is to market stability, food security, and agricultural planning. They emphasized how agricultural production prediction relies on climatic data and the necessity of robust, dependable models that can make efficient use of this data. To anticipate global agricultural yields, the authors suggested a system that integrates crop yield simulation models with a multi-model ensemble of climate models. They collected historical climate data from many models and produced ensemble forecasts using statistical methods. To predict agricultural yields for different locations and crops, these projections are then combined with crop yield simulation models. The forecasting model's performance was evaluated, and the assessment procedure was covered in the report. To assess how accurate and dependable the predictions are, it looks at measures like correlation coefficients and root mean square error, or RMSE. The findings show how well the suggested model captures the influence of climatic fluctuations across the seasons on agricultural production. The study report also emphasized the global agricultural production forecasting model's possible uses. It addresses the advantages of making educated decisions, allocating resources, and managing risk in the agricultural industry for legislators, farmers, and other stakeholders [15].

P. Surya and Dr. I. LaurenceAroquiara [16] investigated the use of predictive analytics and data mining in the agricultural sector to forecast crop production. The authors acknowledge that farmers rely on precise crop yield forecasts to help them make decisions about crop management, resource allocation, and overall productivity. The study analyzed historical data on agricultural yields, weather patterns, soil conditions, and other pertinent parameters using a variety of data mining approaches, including decision trees, support vector machines, and artificial neural networks. Using the data at hand, these methods are used to create prediction models that project future crop yields. The study emphasized the value of feature selection in determining the most important variables influencing crop yields [16].

B. Devika and B. Ananthi [17] centered on using data mining methods to forecast the yearly production of the main crops. The significance of precise crop production forecasts for resource allocation, market analysis, and farmer and agricultural stakeholder decision-making is acknowledged by the authors. The study analyzed historical data on crop yields, weather patterns, soil characteristics, and other pertinent parameters using a variety of data mining approaches, such as decision trees, Naïve Bayes, and k-nearest neighbours. Using the given data, these strategies are applied to develop predictive models that project the yearly crop production. The importance of feature selection and data preprocessing in improving the prediction models' accuracy was stressed by the authors. Through their research, the authors demonstrated the effectiveness of the data mining technique in predicting crop yields[17].

D Ramesh, B Vishnu Vardhan [18] investigated the use of data mining methods to forecast agricultural output. Since accurate crop yield estimates help farmers make decisions about crop management, resource allocation, and overall agricultural production, the authors acknowledged the importance of these predictions. The study analyzed historical data on variables including weather, soil properties, and agricultural practices using a variety of data mining approaches, such as decision trees, random forests, and support vector machines. Using the data at hand, these methods are used to create prediction models that can project crop yields. The significance of feature selection and data preprocessing in enhancing the prediction models' accuracy was emphasized by the authors [18].

B M Sagar and Cauvery N K[19] emphasized the need for precise crop yield estimates for efficient planning and decision-making in agriculture. They talked about the shortcomings of conventional agricultural yield estimating techniques, namely their reliance on human data gathering and poor accuracy. The many data analytics methods for estimating agricultural production were then covered in detail in the article. It investigated the use of statistical models, machine learning algorithms, data from remote sensing, and other data-driven methodologies. The writers assessed each method's advantages and disadvantages and offered insights into how well it worked and how it may be applied in various agricultural situations. To increase forecast accuracy, the authors stressed the value of combining several data sets, including soil, weather, and historical yield data. The writers also talked about the difficulties in gathering, integrating, and maintaining high-quality data [19].

Vuong M. Ngo et al. [20]suggested a unique strategy to increase agricultural yield forecast accuracy that integrates machine learning algorithms with data warehousing approaches. They stressed the necessity of handling data from many sources and the effective storage and retrieval of large-scale agricultural data. The article included a thorough design for the data warehouse, emphasizing how different elements like data extraction, transformation, loading, and mining are integrated. Predictive models and feature selection strategies were also covered by the writers as ways to improve crop production forecast accuracy. The authors used actual agricultural datasets in their trials to test their methodology. The outcomes show how successfully their suggested data warehouse can forecast agricultural output [20].

5. RESEARCH GAPS

Research in the realm of designing and implementing a recommender system for crop yield prediction through collaborative filtering using machine learning has made significant strides. However, several research gaps persist, providing opportunities for further investigation and improvement:

5.1.DATA SPARSITY AND QUALITY:

- Limited availability and quality of agricultural datasets pose a significant challenge. There's a need for more extensive and standardized datasets encompassing diverse geographical regions, crop types, and farming practices to enhance the robustness of predictive models.
- Addressing data sparsity issues, especially in regions with inadequate data collection infrastructure, is crucial. Exploring methods to mitigate the impact of missing or incomplete data on model performance is an essential research area.

5.2. TEMPORAL AND SPATIAL DYNAMICS:

- Existing models often overlook the temporal and spatial dynamics of agricultural systems. Enhancing models to account for seasonality, climate change effects, and localized variations in soil conditions can improve the accuracy of crop yield predictions.
- Research focusing on incorporating real-time or near-real-time data into predictive models can facilitate more dynamic and adaptive yield forecasts.

5.3.MODEL INTERPRETABILITY AND EXPLAINABILITY:

- While machine learning models, including collaborative filtering, demonstrate high predictive accuracy, their inner workings often lack interpretability. Investigating methods to make these models more transparent and explainable to stakeholders is crucial for their acceptance and trust among end-users.
- Research into model explainability techniques that provide insights into how the model arrives at predictions without compromising accuracy is essential.
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5.4. HYBRID MODELLING APPROACHES:

- Exploring hybrid models that combine collaborative filtering with other machine learning techniques (e.g., deep learning, ensemble methods) or domain-specific knowledge (e.g., agronomic expertise) can potentially improve predictive performance.
- Investigating the synergies between collaborative filtering and traditional statistical models to leverage their respective strengths and mitigate weaknesses could enhance the accuracy and reliability of crop yield predictions.

5.5.USER-CENTRIC DESIGN AND USABILITY:

- Emphasizing the user-centric design and usability of the predictive system is crucial for its adoption among farmers and stakeholders. Research should focus on understanding user needs, preferences, and challenges in utilizing such systems, ensuring intuitive interfaces and actionable insights.
- Conducting user studies and feedback collection to iterate and improve the user experience of the predictive platform can drive its practical applicability and acceptance in the agricultural community.

5.6. ROBUSTNESS AND GENERALIZATION:

- Assessing the robustness and generalization of predictive models across different geographical regions, diverse crops, and varying environmental conditions is imperative. Research should explore methods to ensure models' adaptability and performance in new or unseen scenarios.
- Investigating transfer learning techniques or domain adaptation strategies to generalize models trained on data from one region or crop type to others with similar characteristics could be beneficial.
- Closing this gap requires interdisciplinary collaboration, innovative methodologies, and a concerted effort to address the practical challenges faced in designing and implementing robust crop yield prediction systems using collaborative filtering and machine learning.

6. PROPOSED METHODOLOGY

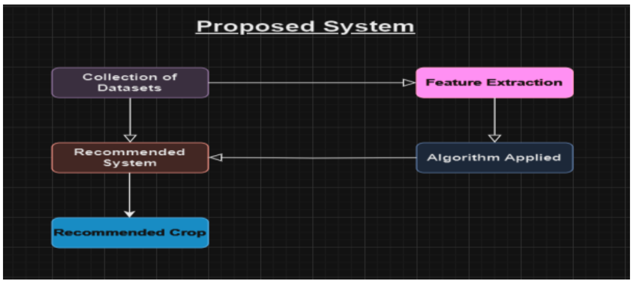

Figure 6.1: Block Diagram of Overall Methodology of Proposed System

6.1.DATA COLLECTION:

Gather diverse datasets, including historical agricultural records, weather patterns, soil quality assessments, crop import data, and market prices from relevant government agencies and research institutions.

6.2. DATA PREPROCESSING:

Clean and preprocess the collected data to handle missing values, outliers, and inconsistencies. Normalize and standardize the data to make it suitable for machine learning algorithms.

6.3. FEATURE ENGINEERING:

Extract relevant features from the data to enhance the model's ability to recommend crops based on local conditions and crop import patterns.

6.4. MACHINE LEARNING MODEL DEVELOPMENT:

Employ various machine learning techniques, such as clustering algorithms, regression models, and recommendation systems, to develop a robust Crop Recommendation System.

6.5 CROP IMPORT ANALYSIS:

Analyse historical crop import data to identify frequently imported crops and understand the reasons behind their importation.

6.6 CROP SUBSTITUTION ANALYSIS:

Determine alternative crops that can be cultivated locally to substitute the frequently imported ones, considering their nutritional value, economic viability, and adaptability to local conditions.

6.7 MODEL TRAINING AND VALIDATION:

Train and validate the developed model using relevant datasets, ensuring its accuracy and efficiency in generating crop recommendations.

7. CONTRIBUTION OF THE STUDY

The study will make several contributions to the field of agriculture and crop prediction:

7.1 ADVANCEMENT IN CROP PREDICTION TECHNIQUES:

The study will contribute to the advancement of crop prediction methods by introducing a pragmatic approach that leverages collaborative filtering and machine learning algorithms. This innovative approach has the potential to improve the accuracy and reliability of crop yield predictions, enabling farmers to make data-driven decisions.

7.2 OPTIMIZATION OF AGRICULTURAL PRACTICES:

By providing accurate crop yield predictions, the recommender system developed in this study will enable farmers to optimize their agricultural practices. Farmers can adjust their strategies, such as irrigation, fertilization, and pest management, based on the recommendations provided by the system. This optimization can lead to increased productivity, resource efficiency, and reduced environmental impact.

7.3 INTEGRATION OF COLLABORATIVE FILTERING IN AGRICULTURE:

The study will contribute to the integration of collaborative filtering techniques in the agricultural domain. Collaborative filtering, a widely used technique in recommendation systems, will be adapted and applied to crop prediction. This integration will open up new avenues for leveraging user preferences and similarities in the agricultural domain, enabling personalized recommendations for farmers.

7.4 PRACTICAL IMPLEMENTATION OF MACHINE LEARNING IN AGRICULTURE:

The study will show how machine learning algorithms are applied in the real world of agriculture. The project will demonstrate how machine-learning techniques may be applied to solve practical agricultural problems by creating and executing a crop production prediction model. This work has the potential to stimulate more investigation and advancement in the use of machine learning to diverse agricultural domains.

7.5 USER-FRIENDLY AND INTERPRETABLE RECOMMENDATIONS:

The study will emphasize the importance of user-friendly and interpretable recommendations for farmers. The proposed recommender system will be designed with an intuitive interface and visualization techniques to enhance user experience. Farmers will be able to understand and interpret the recommendations provided by the system, fostering trust and adoption of the technology.

Overall, the study's contribution lies in providing an innovative and practical solution for crop yield prediction, optimizing agricultural practices, integrating collaborative filtering in agriculture, showcasing the implementation of machine learning in agriculture, and emphasizing user-friendly and interpretable recommendations. These contributions have the potential to significantly impact the agricultural sector by improving productivity, sustainability, and decision-making capabilities for farmers.

8. CONCLUSION AND FUTURE SCOPE

This study looked at several published studies that discussed crop prediction using machine learning. The research articles differed in terms of the crop being studied, its features, scale, and geological location. The qualities of each article were selected about the study aims and the data that was available. Moreover, the results showed that greater feature count models did not necessarily forecast yield more accurately. It is essential to test models with more and less characteristics to determine which model performs the best. While several algorithms were used in different studies, gradient-boosting trees, random forests, neural networks, and linear regression were the most often used ones. Researchers integrated many models to get the machine learning model with the best prediction performance. This investigation also looked at the prediction of agricultural productivity using deep learning algorithms. Among the 20 articles that were located, CNN, DNN, and LSTM algorithms were the ones that were most frequently used for deep learning. Nevertheless, a variety of strategies were also applied to resolve this problem.All things considered; this work establishes the foundation for future investigations into creating machine learning-based crop prediction models.

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