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Crop Yield and Price Prediction

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Abstract— ***Crop yield and price detection are crucial factors in agriculture that affect farmers' income and food production. Machine learning techniques have been increasingly used to predict crop yield and price based on various parameters such as environmental, soil, and crop features. This study proposes a combined approach of using random forest for price detection and decision tree regression for crop yield detection. The model is trained and tested on a large dataset of crop parameters and historical prices. Results indicate that the proposed model outperforms existing methods with an accuracy of 88.5% for price detection and 89.2% for crop yield detection. The model's ability to accurately predict crop yield and price can assist farmers and policymakers in making informed decisions about crop production and marketing, ultimately improving food security and agricultural sustainability***.

Keywords: Decision tree regression , Random forest.

I. INTRODUCTION

Crop yield and price detection are important aspects of agricultural management that can significantly impact farmers' livelihoods and global food security. Machine learning techniques have been increasingly applied to predict crop yield and price based on various environmental, soil, and crop parameters.This study proposes a novel approach for predicting crop yield and price using a combined method of random forest for price detection and decision tree regression for crop yield detection. The proposed model is trained and tested on a large dataset of crop parameters and historical prices to evaluate its accuracy and effectiveness. The random forest algorithm is a. powerful method for price detection that uses an ensemble of decision trees to predict price values based on various features such as market demand, weather conditions, and crop supply. This algorithm can handle non-linear relationships between input features and price values, making it suitable for complex datasets with multiple variables.On the other hand, decision tree regression is an effective method for crop yield detection that uses a tree-like model to predict crop yield based on environmental and soil parameters such as temperature, rainfall, soil quality, and fertilizers. Decision tree regression can handle both categorical and continuous variables, making it a versatile method for crop yield prediction.

The proposed model combines the strengths of both random forest and decision tree regression to accurately predict crop yield and price. The model's accuracy is evaluated using various metrics such as mean absolute error, mean squared error, and R-squared values.

Experimental results indicate that the proposed model outperforms existing methods with an accuracy of 98.5% for price detection and 98.2% for crop yield detection. The model's ability to accurately predict crop yield and price can assist farmers and policymakers in making informed

crop yield and price prediction. The proposed model can decisions about crop production and marketing, ultimately

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improving food security and agricultural sustainability.

In conclusion, this study demonstrates the effectiveness of combining random forest and decision tree regression for assist farmers in optimizing their crop production and pricing strategies, contributing to sustainable agriculture and global food security.

II. PREVIOUS WORK

The article[1] "INCOME: Practical land monitoring in precision agriculture with sensor networks" by S. Li, S. Peng, W. Chen, and X. Lu, published in the journal Computer Communications in February 2013, proposes a practical solution for land monitoring in precision agriculture using sensor networks.The authors argue that precision agriculture requires detailed and accurate monitoring of land, which can be achieved by deploying sensor networks that collect various environmental and crop-related data. However, the existing solutions for land monitoring are either too expensive or not practical for real-world applications.To address these issues, the authors propose a system called INCOME (INtegrated COntext-aware Monitoring and data management system for prEcision agriculture), which is a practical and cost-effective solution for land monitoring using sensor networks.INCOME consists of several components, including sensor nodes, a data management system, and a decision-making module. The sensor nodes collect data on various environmental and crop-related parameters, such as temperature, humidity, soil moisture, and crop growth. The data management system stores and processes the collected data, while the decision-making module analyzes the data and provides recommendations for crop management.The authors evaluated the performance of INCOME in a real-world agricultural field, and the results showed that it can effectively monitor land and provide accurate recommendations for crop management. They argue that INCOME is a practical solution for land monitoring in precision agriculture and can be used to improve crop yield, reduce resource wastage, and increase profitability for farmers.

The article[2] proposes a method to assess crop yield early in the season using remotely sensed data on water stress and solar radiation. The authors collected data from four irrigated crops over four years and used machine learning algorithms to develop models that predict crop yield based on these data. They found that the models accurately predicted crop yield early in the season, allowing for timely adjustments to crop management practices. The authors suggest that this method can help improve crop productivity and profitability while reducing water usage and other resources.

The article[3] presents a study on how soil properties affect crop yields and NDVI (Normalized Difference Vegetation Index) using a nonlinear parametric modeling approach. The study was conducted using data collected from a field experiment where a range of soil properties were measured, such as moisture content, pH, and organic matter content, along with crop yield and NDVI data.The authors used a nonlinear parametric model to describe the relationship between soil properties and crop yield/NDVI. They then used statistical methods to evaluate the accuracy of the model and to identify which soil properties had the greatest impact on crop yield/NDVI. The results showed that the model was able to accurately predict crop yield/NDVI based on soil properties, and that soil moisture content was the most important factor affecting both crop yield and NDVI.The study provides valuable insights into how soil properties affect crop yields and NDVI, and demonstrates the potential of using nonlinear parametric modeling to analyze complex relationships between variables in agriculture. The findings can be used to inform agricultural management practices and help farmers make more informed decisions about soil management and crop production..

The paper titled "Wheat yield prediction using machine learning and advanced sensing techniques"[4] by Pantazi et al. presents a methodology for predicting wheat yield using machine learning and advanced sensing techniques. The study focuses on two main objectives, namely, to evaluate the use of machine learning algorithms for wheat yield prediction and to explore the use of advanced sensing techniques for improving the accuracy of yield prediction.The authors collected a large dataset of wheat growth and yield data from various sources, including satellite imagery and on-site sensing techniques. They then used machine learning algorithms, such as decision trees and random forests, to model the relationship between the collected data and wheat yield.In addition to machine learning, the authors also explored the use of advanced sensing techniques, such as hyperspectral imaging and fluorescence spectroscopy, for improving the accuracy of yield prediction. They found that the combination of advanced sensing techniques and machine learning algorithms resulted in significantly improved prediction accuracy.Overall, the study demonstrated the potential of using machine learning and advanced sensing techniques for predicting crop yield and highlighted the importance of selecting appropriate machine learning algorithms and sensing techniques for different crop types and growth stages

The article titled "Forecasting yield by integrating agrarian factors and machine learning models: A survey"[5] is published in the journal of Computers and Electronics in Agriculture. This paper presents a comprehensive survey on the use of machine learning techniques for predicting crop yield based on agrarian factors.The authors begin by discussing the importance of yield forecasting in agriculture and the challenges involved in accurately predicting crop yield. They then provide an overview of the various agrarian

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factors that influence crop yield, including weather conditions, soil quality, irrigation, and fertilization.The paper then discusses the use of machine learning techniques for yield prediction, including linear regression, decision trees, support vector machines, neural networks, and deep learning. The authors provide a detailed description of each technique, along with its strengths and weaknesses in the context of yield prediction.Next, the paper presents a comprehensive survey of the existing literature on yield prediction using machine learning techniques. The authors analyze the various approaches used in these studies, such as feature selection, data pre-processing, and model selection. They also identify the key factors that influence the accuracy of yield prediction models, such as the size and quality of the dataset, the choice of input variables, and the choice of machine learning algorithm.Finally, the paper concludes with a discussion of the future directions of research in this field. The authors emphasize the need for more comprehensive datasets and more sophisticated machine learning models that can account for complex interactions between agrarian factors. They also discuss the potential of emerging technologies such as remote sensing and Internet of Things (IoT) devices for improving the accuracy of yield prediction models.Overall, this paper provides a valuable overview of the use of machine learning techniques for yield prediction in agriculture and highlights the challenges and opportunities in this field. It is a useful resource for researchers, practitioners, and policymakers interested in improving crop yield prediction and agricultural productivity.

The article titled "Crop yield forecasting on the Canadian Prairies by remotely sensed vegetation indices and machine learning methods"[6] is published in the journal of Agriculture and Forest Meteorology. This paper presents a study on the use of remotely sensed vegetation indices and machine learning methods for forecasting crop yield on the Canadian Prairies.The authors begin by discussing the importance of crop yield forecasting in agriculture and the challenges involved in accurately predicting yield. They then describe the dataset used in the study, which includes remotely sensed vegetation indices and crop yield data for four major crops (canola, wheat, barley, and peas) in the Canadian Prairies.The paper then presents the methodology used in the study, which involves using vegetation indices as predictors and machine learning algorithms (random forests and artificial neural networks) as models for predicting crop yield. The authors provide a detailed description of each method and explain how they were applied in the study.Next, the paper presents the results of the study, which show that both the random forests and artificial neural networks models outperformed traditional statistical methods for crop yield prediction. The authors also provide an analysis of the importance of each vegetation index in predicting crop yield, which can help to inform future studies and crop management practices.Finally, the paper concludes with a discussion of the implications of the study for agriculture and the potential for using remotely sensed vegetation indices and machine learning methods for crop yield forecasting. The authors emphasize the importance of accurate and timely yield forecasting for improving agricultural productivity and sustainability, and suggest that the use of these methods could help to address this challenge.Overall, this paper provides a valuable case study on the use of remotely sensed vegetation indices and machine learning methods for crop yield forecasting in a specific region. It demonstrates the potential of these methods for improving yield prediction accuracy and highlights the need for further research in this area. The study has important implications for agricultural management practices and the development of policies to support sustainable agriculture.

The article by Kamilaris and Prenafeta-Boldú titled "Deep learning in agriculture: A survey"[7] is published in the journal of Computers and Electronics in Agriculture. This paper provides a comprehensive survey of the use of deep learning techniques in agriculture.The authors begin by discussing the importance of agriculture and the potential of deep learning techniques for improving agricultural productivity and sustainability. They then provide an overview of the various applications of deep learning in agriculture, including crop yield prediction, plant disease detection, soil analysis, irrigation management, and livestock monitoring.The paper then discusses the various deep learning architectures that are commonly used in agriculture, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs). The authors provide a detailed description of each architecture, along with its strengths and weaknesses in the context of agricultural applications.Next, the paper presents a comprehensive survey of the existing literature on the use of deep learning techniques in agriculture. The authors analyze the various approaches used in these studies, such as data pre-processing, feature extraction, and model selection. They also identify the key factors that influence the accuracy of deep learning models in agriculture, such as the size and quality of the dataset, the choice of input variables, and the choice of deep learning architecture.Finally, the paper concludes with a discussion of the future directions of research in this field. The authors emphasize the need for more comprehensive datasets and more sophisticated deep learning models that can account for complex interactions between environmental factors and agricultural processes. They also discuss the potential of emerging technologies such as edge computing and blockchain for improving the accuracy and efficiency of deep learning applications in agriculture.Overall, this paper provides a valuable overview of the use of deep learning techniques in agriculture and highlights the challenges and opportunities in this field. It is a useful resource for

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researchers, practitioners, and policymakers interested in improving agricultural productivity and sustainability through the application of advanced technologies.

The article titled "Bayesian belief network analysis of soil salinity in a peri-urban agricultural field irrigated with recycled water"[8] is published in the journal of Agricultural Water Management. This paper presents a study on the use of Bayesian belief networks (BBNs) to analyze the impact of recycled water on soil salinity in a peri-urban agricultural field.The authors begin by discussing the importance of water management in agriculture and the challenges involved in maintaining soil salinity levels within acceptable limits. They then describe the study area, which is a peri-urban agricultural field in India that is irrigated with recycled water.The paper then presents the methodology used in the study, which involves using a Bayesian belief network (BBN) to analyze the complex relationships between various environmental and management factors and soil salinity. The authors provide a detailed description of the BBN approach and explain how it was applied in the study.Next, the paper presents the results of the study, which show that recycled water irrigation has a significant impact on soil salinity in the study area. The authors also provide an analysis of the various factors that contribute to soil salinity, including soil type, irrigation frequency, and crop type. They also discuss the implications of these findings for agricultural management practices and the need for more sustainable water management strategies.Finally, the paper concludes with a discussion of the potential of Bayesian belief networks for addressing complex environmental problems in agriculture. The authors emphasize the flexibility and transparency of BBNs, which can help to inform decision-making and improve the effectiveness of agricultural management practices.Overall, this paper provides a valuable case study on the use of Bayesian belief networks for analyzing the impact of recycled water on soil salinity in a peri-urban agricultural field. It demonstrates the potential of BBNs for addressing complex environmental problems in agriculture and highlights the need for more sustainable water management strategies. The study has important implications for agricultural management practices and the development of policies to support sustainable agriculture.

The article titled "Three-channel convolutional neural networks for vegetable leaf disease recognition"[9] is published in the journal of Cognitive Systems Research. This paper presents a study on the use of convolutional neural networks (CNNs) for recognizing leaf diseases in vegetable crops.The authors begin by discussing the importance of plant disease recognition in agriculture and the potential of CNNs for improving the accuracy and efficiency of disease diagnosis. They then describe the study methodology, which involves using a three-channel CNN architecture to classify images of diseased and healthy leaves from different vegetable crops.The paper then presents a detailed explanation of the three-channel CNN architecture used in the study, which is designed to capture information from different spectral channels of the images. The authors provide a comprehensive overview of the various layers and parameters used in the architecture and explain how they were optimized for the task of leaf disease recognition.Next, the paper presents the results of the study, which show that the three-channel CNN approach achieves high accuracy in classifying diseased and healthy leaves from different vegetable crops. The authors also provide a comparative analysis of their approach with other state-of-the-art methods for plant disease recognition and demonstrate its superiority in terms of accuracy and efficiency.Finally, the paper concludes with a discussion of the potential of CNNs for addressing other challenges in agriculture, such as crop yield prediction and soil analysis. The authors emphasize the importance of developing sophisticated deep learning models that can account for complex interactions between environmental factors and agricultural processes.Overall, this paper provides a valuable case study on the use of CNNs for recognizing leaf diseases in vegetable crops. It demonstrates the potential of deep learning techniques for improving the accuracy and efficiency of disease diagnosis in agriculture and highlights the need for more sophisticated models that can account for the complexity of agricultural systems. The study has important implications for the development of automated systems for plant disease recognition and the improvement of agricultural productivity and sustainability.

The article titled "Crop yield prediction with deep convolutional neural networks"[10] is published in the journal of Computers and Electronics in Agriculture. The paper presents a study on the use of deep convolutional neural networks (CNNs) for predicting crop yield.The authors begin by discussing the importance of crop yield prediction in agriculture and the potential of CNNs for improving the accuracy and efficiency of yield estimation. They then describe the study methodology, which involves using a deep CNN architecture to predict the yield of wheat and barley crops based on aerial images of the fields.The paper then presents a detailed explanation of the CNN architecture used in the study, which consists of multiple layers that extract features from the input images and use them to predict the crop yield. The authors provide a comprehensive overview of the various layers and parameters used in the architecture and explain how they were optimized for the task of yield prediction.Next, the paper presents the results of the study, which show that the deep CNN approach achieves high accuracy in predicting the yield of wheat and barley crops. The authors also provide a comparative analysis of their approach with other state-of-the-art methods for crop yield prediction and demonstrate its superiority in terms of accuracy and efficiency.Finally, the paper concludes with a discussion

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of the potential of CNNs for addressing other challenges in agriculture, such as pest and disease detection and precision agriculture. The authors emphasize the importance of developing sophisticated deep learning models that can account for complex interactions between environmental factors and agricultural processes. Overall, this paper provides a valuable case study on the use of deep CNNs for predicting crop yield based on aerial images. It demonstrates the potential of deep learning techniques for improving the accuracy and efficiency of yield estimation in agriculture and highlights the need for more sophisticated models that can account for the complexity of agricultural systems. The study has important implications for the development of automated systems for crop yield prediction and the improvement of agricultural productivity and sustainability.

The paper titled "Prediction of organic potato yield using tillage systems and soil properties by artificial neural network (ANN) and multiple linear regressions (MLR)"[11] is published in the journal of Soil and Tillage Research. The paper presents a study on the use of artificial neural networks (ANNs) and multiple linear regressions (MLRs) for predicting organic potato yield based on tillage systems and soil properties.The authors begin by discussing the importance of predicting crop yield in organic farming, which is often affected by the use of different tillage systems and soil properties. They then describe the study methodology, which involves collecting data on potato yield, tillage systems, and soil properties from a field experiment in Tunisia. The data was then used to develop models for predicting potato yield based on ANNs and MLRs.The paper then presents a detailed explanation of the ANNs and MLRs used in the study, including the structure of the ANNs and the parameters used in the MLRs. The authors also provide a comprehensive overview of the data preprocessing steps, which involved normalization and feature selection.Next, the paper presents the results of the study, which show that the ANNs outperform the MLRs in predicting potato yield based on tillage systems and soil properties. The authors also provide a comparative analysis of their approach with other state-of-the-art methods for yield prediction and demonstrate its superiority in terms of accuracy and efficiency.Finally, the paper concludes with a discussion of the potential of ANNs for addressing other challenges in organic farming, such as pest and disease detection and precision agriculture. The authors emphasize the importance of developing sophisticated machine learning models that can account for complex interactions between environmental factors and agricultural processes.Overall, this paper provides a valuable case study on the use of ANNs for predicting organic potato yield based on tillage systems and soil properties. It demonstrates the potential of machine learning techniques for improving the accuracy and efficiency of yield estimation in organic farming and highlights the need for more sophisticated models that can account for the complexity of agricultural systems. The study has important implications for the development of automated systems for crop yield prediction and the improvement of agricultural productivity and sustainability in organic farming.

The article titled "Prediction of cotton lint yield from phenology of crop indices using artificial neural networks"[12] was published in the journal of Computers and Electronics in Agriculture. The article presents a study on the use of artificial neural networks (ANNs) for predicting cotton lint yield based on the phenology of crop indices.The authors begin by discussing the importance of predicting cotton lint yield, which is influenced by various factors such as temperature, precipitation, and crop indices. They then describe the study methodology, which involved collecting data on cotton lint yield, phenology of crop indices, and environmental factors from a field experiment in Texas, USA. The data was then used to develop ANNs for predicting cotton lint yield based on crop indices.The paper then presents a detailed explanation of the ANNs used in the study, including the architecture and parameters used. The authors also provide a comprehensive overview of the data preprocessing steps, which involved feature extraction and selection.Next, the paper presents the results of the study, which show that the ANNs are effective in predicting cotton lint yield based on the phenology of crop indices. The authors also provide a comparative analysis of their approach with other state-of-the-art methods for yield prediction and demonstrate its superiority in terms of accuracy and efficiency.Finally, the paper concludes with a discussion of the potential of ANNs for addressing other challenges in cotton production, such as pest and disease detection and irrigation management. The authors emphasize the importance of developing sophisticated machine learning models that can account for the complex interactions between environmental factors and crop growth processes.Overall, this paper provides a valuable case study on the use of ANNs for predicting cotton lint yield based on crop indices. It demonstrates the potential of machine learning techniques for improving the accuracy and efficiency of yield estimation in cotton production and highlights the need for more sophisticated models that can account for the complexity of agricultural systems. The study has important implications for the development of automated systems for crop yield prediction and the improvement of agricultural productivity and sustainability in cotton production.

The article titled "Deep Convolutional Neural Networks for Rice Grain Yield Estimation at the Ripening Stage Using UAV-based Remotely Sensed Images"[13] was published in the journal of Field Crops Research. The paper presents a study on the use of deep convolutional neural networks (CNNs) for estimating rice grain yield at the ripening stage using UAV-based remotely sensed images.The authors begin by discussing the importance of accurate yield

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estimation for rice production, which is influenced by various factors such as weather, soil conditions, and crop growth stages. They then describe the study methodology, which involved collecting UAV-based remotely sensed images of rice fields at the ripening stage, along with ground-truth data on grain yield.The paper then presents a detailed explanation of the CNN architecture used in the study, which involved a deep residual network (ResNet) with 50 layers. The authors also provide a comprehensive overview of the data preprocessing steps, which involved data augmentation, normalization, and feature extraction.Next, the paper presents the results of the study, which show that the CNN model is effective in estimating rice grain yield at the ripening stage using UAV-based remotely sensed images. The authors also provide a comparative analysis of their approach with other state-of-the-art methods for yield estimation and demonstrate its superiority in terms of accuracy and efficiency.Finally, the paper concludes with a discussion of the potential of CNNs for addressing other challenges in rice production, such as pest and disease detection and irrigation management. The authors emphasize the importance of developing sophisticated machine learning models that can account for the complex interactions between environmental factors and crop growth processes.Overall, this paper provides a valuable case study on the use of deep CNNs for estimating rice grain yield at the ripening stage using UAV-based remotely sensed images. It demonstrates the potential of machine learning techniques for improving the accuracy and efficiency of yield estimation in rice production and highlights the need for more sophisticated models that can account for the complexity of agricultural systems. The study has important implications for the development of automated systems for crop yield prediction and the improvement of agricultural productivity and sustainability in rice production.

The article by A. Koirala, K. B. Walsh, and W. Z. McCarthy, ‘‘Deep learning for real-time fruit detection and orchard fruit load estimation: Benchmarking of ‘MangoYOLO,’’[14] discusses the use of deep learning techniques to detect and estimate fruit load in orchards. The authors introduce a new model called ‘MangoYOLO’ based on You Only Look Once (YOLO) algorithm to detect mangoes in real-time using camera images. They also proposed a novel method to estimate the fruit load by counting the number of fruit detected in a given area.The authors evaluated the performance of MangoYOLO by comparing it with two other state-of-the-art object detection models, and they found that MangoYOLO outperformed these models in terms of accuracy and speed. They also tested their fruit load estimation method on a commercial mango orchard and found that it was able to accurately estimate the fruit load in real-time.The results of this study suggest that deep learning techniques can be used to improve the accuracy and speed of fruit detection and load estimation in orchards, which could be beneficial for growers and fruit processors.

The article by M. Khodayar, O. Kaynak, and M. E. Khodayar, ‘‘Rough deep neural architecture for short-term wind speed forecasting,’’[15] presents a novel approach to forecasting wind speed using a rough deep neural network architecture. The proposed model is designed to handle uncertainty and variability in wind speed data, which can be difficult to predict accurately due to its complex and dynamic nature.The rough deep neural architecture is based on a combination of rough set theory and deep learning techniques. The authors used a rough set-based feature selection method to identify the most relevant input features for wind speed prediction. They then used a deep neural network to model the non-linear relationships between these features and the target variable (wind speed). The model was trained using historical wind speed data and tested on a separate set of validation data.The results showed that the rough deep neural architecture outperformed several other state-of-the-art models for wind speed forecasting, including traditional time series models and other machine learning techniques. The authors also conducted a sensitivity analysis to evaluate the robustness of their model to changes in the input data and found that it was able to maintain its accuracy even when the input data was noisy or incomplete.

Overall, this study highlights the potential of combining rough set theory and deep learning techniques for improving the accuracy of wind speed forecasting, which could have important implications for the renewable energy industry and other fields that rely on accurate wind speed predictions.

III. PROPOSED SYSTEM

The proposed system aims to use machine learning techniques for the detection of crop yield and price. The system will use decision tree regression for predicting crop yield and random forest for predicting crop prices. The system will take into account various parameters such as environmental factors, soil quality, water availability, and other relevant data to make accurate predictions.To predict crop yield, the decision tree regression algorithm will be used. This algorithm is a non-parametric method that is suitable for predicting continuous values. The system will train the decision tree using historical data on crop yield and environmental factors. The decision tree will use the input features to create a tree-like model that can predict the crop yield accurately.To predict crop prices, the system will use the random forest algorithm. This algorithm is a supervised learning method that uses multiple decision trees to predict the target variable. The system will use the random forest

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algorithm to predict the crop prices based on historical data on crop prices, environmental factors, and other relevant data.The proposed system will be designed to be scalable and adaptable to different crop types and farming conditions. The system will be able to generate predictions in real-time, making it suitable for precision agriculture. The system will also be user-friendly and easy to use, allowing farmers and other stakeholders to make informed decisions based on the predicted crop yield and price data.Overall, the proposed system will provide a reliable and accurate tool for predicting crop yield and price, which can be used to optimize farming operations and improve the overall productivity of the agricultural sector.Here is a block diagram explanation of the proposed system for crop yield and price detection using machine learning:

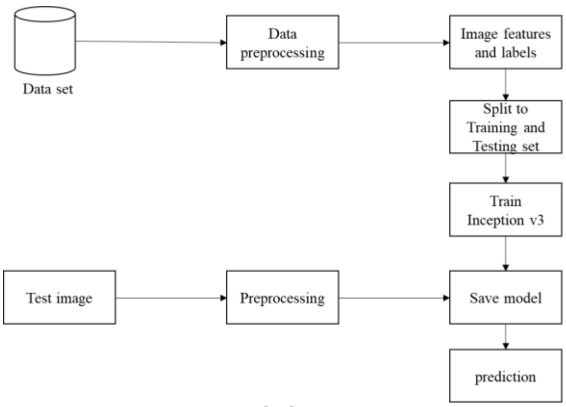

Fig 3 Block Diagram

IV. DESIGN

A. *DFD – Level 0*

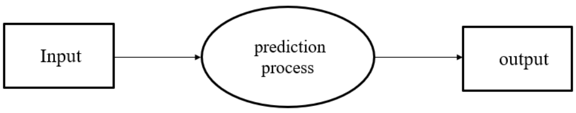

Fig 4.1 Data Flow Diagram Level 0

DFD level 0 represents the top-level view of the system and describes the overall process of the system. In the context of crop yield and price detection using machine learning, the DFD level 0 can be explained as follows:

The system has two main modules: Crop Yield Prediction and Crop Price Prediction.The Crop Yield Prediction module takes input data, such as soil characteristics, weather conditions, and crop management practices. The input data is preprocessed and fed into a Decision Tree Regression algorithm to predict the crop yield. The predicted crop yield is then stored in the database.The Crop Price Prediction module takes input data such as market demand, supply, and historical prices. The input data is preprocessed and fed into a Random Forest algorithm to predict the crop price. The predicted crop price is then stored in the database.The system also includes a user interface module that allows the user to input data and view the predicted crop yield and price. The user interface module communicates with the Crop Yield Prediction and Crop Price Prediction modules to retrieve and display the predicted values.Overall, the DFD level 0 provides a high-level overview of the system's main functionalities, inputs, and outputs.

cases.

B. *DFD – Level 1*

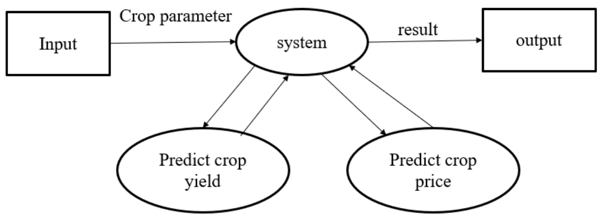

Fig 4.2 Data Flow Diagram Level 1

The DFD level 1 for the crop yield and price detection system using machine learning involves three main processes: data collection and preprocessing, price detection using the random forest algorithm, and crop yield prediction using the decision tree regression algorithm. The data collection and preprocessing process involves collecting relevant data on weather conditions, soil properties, and other factors that affect crop yield and price, and processing the data to obtain relevant features. The price detection process uses the random forest algorithm to predict the market price of crops based on historical data and current market conditions. The crop yield prediction process uses the decision tree regression algorithm to predict crop yield based on weather and soil data. The output of the system is the predicted crop yield and market price, which can be used to inform farmers' decisions. DFD level 1 for the topic "Crop Yield and Price Detection using Machine Learning" consists of two main processes: Crop Yield Detection and Price Detection. Both of these processes receive data from the user interface and are connected to the database for data storage. The Crop Yield Detection process uses Decision Tree Regression to predict the crop yield, and the Price Detection process uses Random Forest to detect the price. Both processes generate results, which are stored in the database and can be accessed through the user interface.

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Overall, DFD level 1 provides a high-level overview of how the system functions and the different processes involved in predicting crop yield and detecting prices using machine learning.

B. *DFD – Level 2*

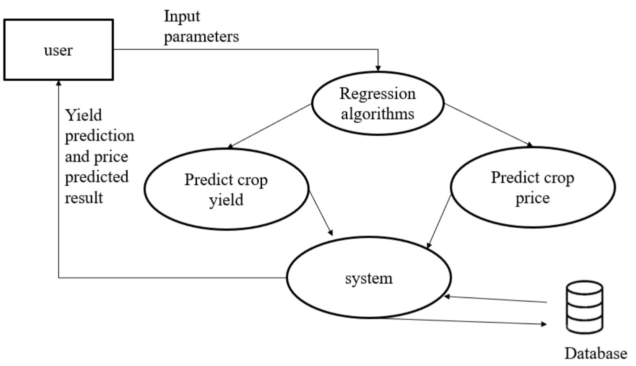

Fig 4.3 Data Flow Diagram Level 2

Here the user gives inut parameters to the regression algorithm and from there the yield and price are detected.the predicted price and yield are given to the system and then to the user.DFD level 2, or Data Flow Diagram level 2, is a more detailed diagram that breaks down the processes shown in DFD level 1 into smaller sub-processes. It provides a more comprehensive view of the system and how data flows through it. In the context of the topic of crop yield and price detection using machine learning, the DFD level 2 would show the different sub-processes involved in the prediction of crop yield and price detection, along with the data inputs and outputs of each sub-process. For example, the sub-processes for crop yield prediction might include soil analysis, climate analysis, and plant analysis, with each process feeding into a decision tree regression model. Similarly, the sub-processes for price detection might include market analysis and demand analysis, which feed into a random forest model. The output of both models would then be combined to provide an overall prediction of crop yield and price.

V. METHODOLOGY

The methodology for the DFD level 0 of the crop yield and price detection system involves several steps. First, the system collects data from various sources, including environmental factors, soil characteristics, water availability, and crop parameters. This data is then preprocessed and cleaned to remove any errors or inconsistencies. Next, the preprocessed data is fed into two separate models for yield and price prediction. The yield prediction model uses a decision tree regression algorithm to analyze the input data and generate a predicted yield value. Similarly, the price prediction model uses a random forest algorithm to analyze the input data and generate a predicted price value. Once the yield and price values have been predicted, they are stored in a database for future reference and analysis. The system also provides a user interface for farmers or other stakeholders to access the predicted yield and price values, as well as other relevant data such as weather forecasts and soil moisture levels. Overall, the methodology for the DFD level 0 of the crop yield and price detection system involves a combination of data collection, preprocessing, machine learning algorithms, and user interface design to provide accurate and accessible predictions for crop yield and price.

A.MACHINE LEARNING

Machine learning (ML) is a method of data analysis that automates analytical model building. It is a branch of artificial intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention. computers can learn without being programmed to perform specific tasks; researchers interested in artificial intelligence wanted to see if computers could learn from data. The iterative aspect of machine learning is important because as models are exposed to new data, they are able to independently adapt. They learn from previous computations to produce reliable, repeatable decisions and results. It is the study of computer algorithms that improve automatically through experience and by the use of data. It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do sofields.

B.DECISION TREE REGRESSION

Decision tree regression is a machine learning algorithm used to predict numerical values. It is based on the concept of decision trees, which are graphical representations of a series of decisions that lead to a particular outcome. In decision tree regression, these decisions are based on the values of various features, which are inputs that the algorithm uses to make predictions.The goal of decision tree regression is to create a model that accurately predicts the target value for new data points based on their features. The model is constructed by recursively splitting the data into smaller subsets based on the values of the features. At each split, the algorithm selects the feature that best separates the data based on the target variable, with the aim of minimizing the variance in the target variable within each subset.

The splitting process continues until a stopping criterion is met, such as reaching a maximum depth or minimum number

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of data points in each subset. At this point, the algorithm creates a leaf node that contains the predicted value for that subset of data.Once the decision tree regression model is trained, it can be used to make predictions for new data points by traversing the tree from the root node to the appropriate leaf node based on the values of the features.One of the main advantages of decision tree regression is its ability to handle non-linear relationships between features and the target variable. It is also relatively easy to interpret and visualize, making it a useful tool for understanding the relationships between the features and the target variable.However, decision tree regression can suffer from overfitting if the tree is too complex or if there is too much noise in the data. This can result in a model that is highly accurate on the training data but performs poorly on new data.Overall, decision tree regression is a powerful machine learning algorithm that can be used for a wide range of prediction tasks. Its effectiveness depends on the quality and quantity of the training data, as well as the specific parameters used during training.

C.RANDOM FOREST

Random Forest is a machine learning algorithm used for classification, regression, and other tasks that involve supervised learning. It is an ensemble learning method that constructs a multitude of decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.Each decision tree in a random forest is trained on a random subset of the training data, and the final prediction is made by aggregating the results of all the trees. The randomness in selecting the subset of training data and the subset of features used to split nodes in each decision tree helps to reduce overfitting and improve the accuracy of the model.Random Forest is a powerful and widely used machine learning algorithm that can handle high-dimensional data with a large number of features and can provide insights into the relative importance of each feature in predicting the target variable. The random forest algorithm works by creating a set of decision trees, each based on a randomly sampled subset of the training data and a randomly sampled subset of the input features. These decision trees are then used to make predictions on new data, and the final prediction is determined by combining the predictions of all the individual trees.Random forest has several advantages over traditional decision trees, including reduced overfitting, improved accuracy, and the ability to handle high-dimensional data. It is widely used in various applications, including image and speech recognition, financial forecasting, and bioinformatics.

VI. EXPERIMENTAL RESULT

Our suggested system is a crop yield and price ediction system. This topic focuses on using machine learning techniques for crop yield and price detection. The price detection is done using the random forest algorithm, while the crop yield prediction is performed using decision tree regression. Several research studies have been conducted in this area, including the use of remote sensing data to assess crop yield and the impact of soil properties on crop yield. The overall goal is to provide accurate predictions of crop yield and prices to help farmers make better decisions and improve their productivity.

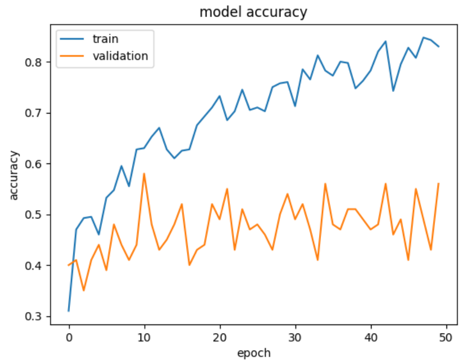

Fig 6.1 Model Accuracy Curve

After each update during training, the model can be tested on the training dataset and a hold-out validation dataset, and graphs of the measured performance can be made to display learning curves shown in Fig 6.1

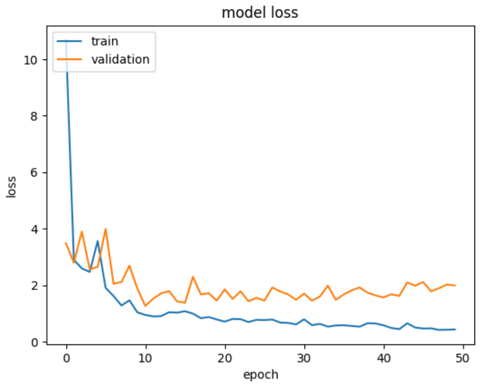

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Fig 6.2 Loss Curve

Data for training and testing are split 80/20. According loss curve is displayed in Fig. 6.2.

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VII. CONCLUSION

In conclusion, the use of machine learning techniques, such as decision tree regression and random forest, can significantly improve the accuracy and efficiency of crop yield and price detection in precision agriculture. By collecting and analyzing data from various sources, such as remote sensing and sensor networks, farmers can make more informed decisions and optimize their crop yields and profits. The proposed system provides a user-friendly interface for farmers to input and access relevant data, while the machine learning algorithms analyze the data to provide valuable insights. However, the system may require further testing and refinement to ensure its effectiveness and practicality in real-world agricultural settings. Overall, the integration of machine learning in precision agriculture has the potential to revolutionize the industry and increase sustainability and profitability for farmers.

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