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REVOLUTIONIZING WHEAT FARMING IN ARID REGIONS WITH MACHINE-LEARNING ENABLED CLOUD COMPUTING FOR YIELD SIMULATION

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ABSTRACT

This research provides a thorough examination of the application of machine learning enabled cloud computing for revolutionising wheat farming in dry environments. The study aims to address the issues that farmers in these areas confront, such as erratic weather patterns, water shortages, and poor soil quality. The suggested method is creating a model that can estimate crop yields reliably based on previous weather data, soil quality, and other environmental parameters. To accomplish this aim, the study team used machine learning techniques like as neural networks to train the model on a vast collection of historical weather and yield data. The model was subsequently incorporated into a cloud computing platform, enabling for large- scale simulations and the optimisation of crop management tactics to maximise yields. The study's findings show that the recommended technique is effective in increasing agricultural yields while decreasing water use. The simulation findings show that the model can estimate yields with high accuracy, allowing farmers to make educated crop management decisions. Furthermore, the cloud computing platform allows for real-time crop monitoring, allowing for early interventions in the event of unfavourable weather events or other environmental conditions that may effect yields. Overall, the work has important implications for wheat growing in dry locations, where farmers confront unique problems. The proposed method has the potential to boost agricultural yields, minimise water use, and raise farmers' overall profitability. The study's findings may also be applied to other crops cultivated in dry environments, offering a framework for sustainable farming practises in similar settings.

Keywords: Edge Computing, Artificial Intelligence, Machine Learning.

I. INTRODUCTION

Wheat cultivation is a vital source of income for many communities across the world. Arid regions, on the other hand, provide substantial problems for farmers due to extreme climatic circumstances such as limited water supplies, low soil quality, and unpredictable weather patterns. certain issues can have a major influence on agricultural production, making it difficult for farmers in certain areas to make a living. As a result, novel techniques to improving agricultural yields, reducing water consumption, and promoting sustainable farming practises are required. Recent technological advancements, such as machine learning and cloud computing, have the potential to revolutionise wheat growing in dry locations.

Machine learning algorithms can analyse massive quantities of data and forecast agricultural yields with high accuracy, while cloud computing enables large-scale simulations that can optimise crop management tactics and yield optimisation. Together, these technologies may offer farmers in dry locations with the information they need to make smart crop management decisions and increase their overall profitability. This research focuses on the use of machine learning-enabled cloud computing for yield modelling in desert wheat farming. The study is driven by the need to address the issues that farmers in these locations confront while also promoting sustainable agricultural practises.

The study builds on prior research that utilised machine learning to estimate agricultural yields, but it focuses on merging this method with cloud computing to allow for large-scale simulations. The suggested method is creating a model that can estimate crop yields reliably based on past weather data, soil quality, and other environmental parameters. The model is trained by analysing massive datasets of historical weather and yield data with machine learning methods such as neural networks. The model is then incorporated into a cloud computing platform, allowing large-scale simulations to be run, allowing crop management tactics to be optimised to maximise yields.

The study's goals are to assess the effectiveness of the suggested technique in raising crop yields, lowering water consumption, and enhancing overall farmer profitability. The study's goal is to develop a framework for sustainable farming practises in arid environments that may later be extended to other crops. The rest of the paper is structured as follows: Section 2 presents an overview of relevant work in agricultural yield prediction and cloud computing. Section 3 outlines the study's methodology, including the data sources and machine learning techniques used. Section 4 includes the simulation results as well as an appraisal of the model's performance. Section 5 analyses the findings' significance for wheat growing in dry places and makes recommendations for future study. Finally, Section 6 gives the study's conclusion.

II. LITERATURE SURVEY

Costello, Anthony, et al. [10] Explains us that Agriculture is a vital industry for both human survival and economic growth. However, with the world's population growing, climate change, and water shortages, there is an urgent need to create sustainable and effective agricultural practises. Arid regions are particularly sensitive to the effects of climate change and water scarcity, making agricultural cultivation difficult. To address these challenges, researchers have explored the use of machine learning and cloud computing to enhance crop yield predictions and optimize crop management strategies. These technologies have the potential to revolutionize farming practices by providing accurate predictions of crop yields, optimizing crop management strategies, and reducing water and fertilizer use.

Machine learning and cloud computing have been utilised in several research to improve agricultural output estimates.Yan, Y., Wang, J., Liu, C., Huang, Y., & He, D. (2019) [5], for example, employed a machine learning technique to estimate maize yields in China, attaining an accuracy of more than 80%. Similarly, Liu et al. (2020) predicted rice yields in China with 92% accuracy using cloud computing. Furthermore, various research have looked into the use of machine learning and cloud computing to improve crop management tactics. Lee, J., Lee, S., Kim, S., Park, J., & Hong, S. (2019) [4], for example, employed a machine learning technique to optimise irrigation schedule for tomato crops in Korea, lowering water usage by 34% while maintaining crop productivity. Similarly, Wang, Y., Zhang, H., & Li, B. (2020) [8] optimised nitrogen fertilisation for maize crops in China, lowering fertiliser consumption by 20% while maintaining crop output. Furthermore, several research have looked at the effect of meteorological conditions on agricultural yields. For example, Huang, W., Zhang, J., Yang, X., Chen, Z., & Zhang, Y. (2019) [2] investigated the link between temperature, precipitation, and maize yields in China, discovering that temperature had a greater influence than precipitation. Similarly, Olesen, J. E., Trnka, M., Kersebaum, K. C., Skjelvåg, A. O., Seguin, B., Peltonen-Sainio, P., ... & Mínguez, M. I. (2018) [12] evaluated the influence of meteorological conditions on wheat yields in Europe, discovering that temperature and precipitation had a substantial impact on crop production.

Overall, the research demonstrates that machine learning and cloud computing have the potential to improve agricultural output estimates and optimise crop management practises. These technologies can assist farmers in increasing crop yields, reducing water and fertiliser consumption, and adapting to the effects of climate change and water scarcity in dry areas. The current work adds to this increasing body of research by proving the potential of machine learning-enabled cloud computing to transform wheat farming in dry locations.

III. METHODOLOGY

Data Collection: The first stage in the process is to acquire the relevant data for the research region. This contains meteorological data from the past, soil quality data, and agricultural production statistics. The information is available from a variety of sources, including government agencies, research institutes, and other organisations. The data should be collected over a long enough period to reflect fluctuations in weather patterns and agricultural yields.

Preprocessing: Once the data has been acquired, it must be preprocessed to ensure that it is ready for analysis. This entails eliminating any outliers or missing values, as well as standardising the data so that all variables are on the same scale. Preprocessing is required to guarantee that the data is clean and dependable, as well as that the analysis is correct.

Feature Selection: The most significant variables that impact crop yields are identified using feature selection approaches. Feature selection can assist to minimise the dataset's dimensionality, making the analysis more efficient and less prone to overfitting. Correlation analysis, feature importance analysis, and principal component analysis are examples of feature selection procedures. The chosen characteristics must be relevant to the study and have a meaningful influence on crop yields.

Model Training: The next phase is to train machine learning algorithms to estimate crop yields based on the features that have been identified. Machine learning systems, such as neural networks, may use past data to forecast agricultural yields for various crop management practises. The training method entails splitting the data into training and validation sets and fine-tuning the model parameters to improve performance. The trained model should be able to estimate crop yields reliably for a variety of weather situations and crop management practises.

Large-Scale Simulations: Once trained, the model may be linked into a cloud computing platform and used to run large-scale simulations. In the simulations, the model is performed using historical meteorological data to estimate crop yields for various crop management practises. The simulations may be run for a variety of meteorological situations, allowing farmers to optimise crop management practises and maximise yields. The simulation findings may be utilised to create crop management strategies adapted to the unique conditions of the research location.

Performance Evaluation: The model's performance is measured using a variety of metrics, including mean squared error, mean absolute error, and coefficient of determination. A sensitivity analysis is also performed to identify the most relevant factors influencing crop yields. The performance evaluation assists in determining the model's accuracy and identifying areas for improvement.

IV. PROCEDURE AND SETUP

Procedure:

Data Collection: Collect meteorological and climatic data, soil parameters, crop management strategies, and yield data for wheat cultivation in dry environments. Data may be gathered from a variety of sources, including government organizations, research institutes, and local farmers. The information gathered should be complete, accurate, and up to date.

Data Preprocessing: After collecting the data, it must be cleaned and processed to remove mistakes and inconsistencies. This process entails dealing with missing data, eliminating outliers, and standardising the data format. Preprocessed data should be organised into an appropriate format for future analysis and modelling.

Feature Selection: The following stage is to determine the most important factors that influence wheat output in dry environments. This may be accomplished through the use of statistical techniques such as correlation analysis and feature importance. The chosen characteristics must be relevant and have a considerable influence on wheat output.

Machine Learning Model Selection: Following the selection of features, the next step is to pick a suitable machine learning algorithm depending on the nature of the issue and the available data. Decision trees, random forests, and neural networks are some of the most often utilised yield prediction methods.

Model Training: After deciding on a machine learning algorithm, the model is trained using preprocessed data. The data is divided into training and testing sets, and the model is fitted to the training data. To achieve the highest potential performance, the model should be optimised.

Model Evaluation: Once trained, the model must be assessed using a validation dataset to estimate its performance. This entails comparing projected and actual yield values and computing several assessment metrics such as mean squared error and coefficient of determination.

Cloud Computing Infrastructure Setup: The following stage is to construct a cloud computing infrastructure that will enable the efficient and scalable processing of huge amounts of data. This requires deciding on a cloud service provider, such as Amazon Web Services or Microsoft Azure, and creating virtual machines with the required specifications and software dependencies.

Model Deployment: Following the installation of the infrastructure, the trained machine learning model must be deployed to the cloud platform. Containerization technologies such as Docker and Kubernetes can help with this.

Yield Prediction and Visualization: Once implemented, the model may be used to estimate wheat yield in various dry environments depending on input data. To assist farmers in making educated decisions, expected yields may be visualised using various tools such as charts and maps.

Setup:

Hardware Setup: The cloud computing infrastructure should have one or more virtual machines with enough CPU, RAM,and disc space criteria. The hardware should be chosen according to the amount of data and the complexity of the machine learning model.

Software Setup: Python or R, scikit-learn or TensorFlow, and Docker or Kubernetes should all be included in the software stack. On the virtual computers, the software should be installed and configured.

Data Storage Setup: The data should be kept in a centralised and safe place, such as an S3 bucket or Azure Blob storage. Data storage should be easily accessible and expandable to support enormous volumes of data.

Containerization Setup: To facilitate simple deployment and scaling, the machine learning model should be containerized using Docker or Kubernetes. Container images should be kept in a container registry such as Docker Hub or Azure Container Registry.

Deployment Setup: Using systems like Jenkins or CircleCI, the deployment process should be automated. The deployment should be extensively tested to confirm that the model is working properly.

Visualization Setup: The expected yields may be shown.

V. RESULTS AND DISCUSSION

The study's findings and discussion demonstrated the potential of machine learning-enabled cloud computing to transform wheat farming in dry locations by forecasting crop yields for various weather conditions and crop management practises.. The system was created to simulate crop yields depending on soil moisture content, temperature, and precipitation, as well as to discover the best crop management options for increasing crop yields while reducing water consumption and fertiliser application.

Model Performance Evaluation: Various criteria were used to assess the machine learning model's accuracy in forecasting crop yields under various weather conditions and crop management practises. The mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R-squared) were all measured as part of the performance evaluation. The performance evaluation findings revealed that the machine learning model was extremely accurate in forecasting crop yields. The MSE and MAE of the model were low, suggesting that the predicted values were close to the actual values. The model also has a high R-squared value, indicating that it can explain a considerable percentage of crop output variability. A sensitivity analysis was also performed to discover the most relevant factors influencing crop yields. The research found that soil moisture content, temperature, and precipitation were the most significant elements influencing crop yields. The model effectively predicted crop yields for various levels of soil moisture content, temperature, and precipitation.

Simulation Results Analysis: The simulations were run to forecast crop yields under various crop management practises and meteorological conditions. The simulation results demonstrated that the model can reliably estimate crop yields under a variety of weather situations and crop management practises. The simulations also shown that the model can determine the best crop management techniques for various weather situations, maximising crop yields while minimising water consumption and fertiliser use. The simulations indicated that the best crop management method differs based on the weather. For example, during a drought, the best approach was to reduce irrigation and fertiliser application, and during a rainy spell, the best strategy was to increase irrigation and fertiliser application. The simulation findings may be utilised to create crop management strategies adapted to the unique conditions of the research location. These strategies can assist farmers in optimising crop production and increasing profitability. The system may also be applied to other crops and places, giving agricultural management a varied and unique approach.

VI. EXPERIMENTAL OUTPUT

Increased yield: One of the key aims of this research is to increase wheat crop output in dry locations. The application of machine learning algorithms to analyse and anticipate the ideal wheat growth conditions might result in a large boost in yield. For example, the algorithms might predict the best circumstances for planting and harvesting wheat crops by analysing data on soil moisture, temperature, humidity, and other environmental aspects. Farmers might possibly boost yields and enhance crop quality with more precise predictions of environmental elements and greater control over irrigation and fertilisation.

Reduction in water usage: In dry locations, water is a limited resource, and agricultural practises are frequently a primary source of water use. The adoption of machine learning algorithms might result in large water savings without losing agricultural production. For example, to establish the most effective watering schedule, the algorithms may analyse data on weather patterns, soil moisture, and plant water consumption. Farmers may be able to reduce water consumption while still obtaining good agricultural yields by optimising irrigation schedules and decreasing water waste.

Improved profitability: Farmers' profitability may grow as a result of increased yields and lower water consumption. Farmers may be able to save money and increase income by optimising their growth conditions and decreasing waste. Machine learning algorithms, for example, might assist farmers in identifying the most cost-effective fertilisation and irrigation systems, resulting in decreased production costs and more income.

Enhanced sustainability: Agricultural practises in arid environments are frequently related with environmental deterioration and natural resource depletion. The use of machine learning-enabled cloud computing might possibly improve the sustainability of wheat farming in dry locations by lowering water use and increasing crop yields. For example, the algorithms might assist farmers in reducing their usage of chemical fertilisers and pesticides, resulting in less pollution and soil deterioration.

Better decision-making: Farmers might make better informed judgements about their agricultural practises by employing machine learning algorithms to analyse massive volumes of data. The algorithms could provide real-time data on weather patterns, soil moisture, plant health, and other factors, allowing farmers to make data-driven decisions about when to plant and harvest their crops, how much water and fertiliser to use, and which crop varieties are best suited for their specific region.

Scalability: The usage of cloud computing helps the machine learning algorithms to be more scalable. This implies that the technology might assist farmers of all sizes, from small-scale family farms to huge commercial enterprises. The algorithms might be tailored to a certain location.

VII. FUTURE SCOPE

Development of Customized Models: While the present work used a machine learning model to forecast wheat yields in dry locations, future research may look into developing customised models for specific regions or even individual farms. This would entail gathering local data on soil conditions, weather patterns, and other factors influencing agricultural productivity and utilising it to train machine learning models tailored to each region or farm.

Integration with IoT Devices: The Internet of Things (IoT) is a network of networked devices that can gather and transfer data. Future study might look into how machine learning-enabled cloud computing can be integrated with IoT devices like soil moisture sensors, weather stations, and agricultural monitoring systems. This would enable for real-time data gathering and analysis, allowing farmers to make educated crop management decisions.

Use of Blockchain Technology: By offering a secure, decentralised data ledger, blockchain technology has the potential to increase transparency and traceability in agriculture. Future study might look into combining blockchain technology with machine learning-enabled cloud computing to track agricultural yields, environmental conditions, and other important data. Farmers, customers, and other stakeholders would be able to check the origin and quality of commodities, as well as assure fair pricing.

Collaboration with Farmers and Local Communities: It is critical to include farmers and local populations in the research process to ensure the acceptance and effectiveness of machine learning-enabled cloud computing for yield simulation in dry regions. Future study might look into methods to work with farmers and other stakeholders to co-create solutions that are suited to each region's distinct requirements and difficulties.

Development of Decision-Support Systems: Decision-support systems (DSS) are software tools that help users make decisions based on sophisticated data analysis. Future study might look at developing DSS based on machine learning- enabled cloud computing models to give farmers with real-time crop management suggestions. These DSS might also include economic and environmental elements to assist farmers in making better educated decisions regarding resource utilisation and crop selection.

Commercialization and Scaling: Finally, the economic feasibility and scalability of machine learning-enabled cloud computing for yield modelling in dry environments will determine its success. Future study might look into ways to commercialise and scale the technology, such as through agricultural partnerships, government funding, or venture capital investment. This would allow the technology to reach more farmers, hence increasing agricultural production and food security in dry regions.

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VIII. CONCLUSION

Finally, the research on machine learning- enabled cloud computing for yield modelling has shown that it has the potential to have a revolutionary influence on wheat farming in dry locations. This technology, which combines machine learning models with cloud computing infrastructure, can give farmers with useful insights into crop management and resource allocation. The predictive model created in this work illustrates the accuracy and potential use of machine learning for yield prediction. The model may offer farmers with a thorough picture of their crop yield potential and optimise their farming operations by taking many environmental and management aspects into consideration. Furthermore, the ability to customise models for individual locations and farms provides an exciting opportunity to adjust this technology to local requirements and resources. This might be especially beneficial to smallholder farmers, who frequently lack the money and infrastructure required to deploy innovative farming methods. In terms of real-time data collecting, safe data exchange, and traceability, the combination of IoT devices and blockchain technology provides further benefits. The application of decision-support systems might improve the technology's utility by offering real-time advice on crop management practises and resource allocation. Collaboration with farmers and local communities is critical for the technology's effective implementation and uptake. Researchers can guarantee that the technology matches the individual demands and problems of each location and community by including stakeholders in the development and implementation process. Finally, the commercialization and scaling potential of this technology holds great promise for global food security and sustainable agricultural practises. This technique can help feed a rising population while lowering agriculture's environmental effect by increasing crop yields and resource efficiency. Overall, the research into machine learning- enabled cloud computing for yield modelling in dry environments opens up intriguing possibilities for improving agricultural production and sustainability. Continued R&D in this field has the potential to have a large beneficial influence on food security, environmental sustainability, and economic growth.

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