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AI-Powered Crop Yield Prediction and Optimization

Shashivardhan.L[1], Pavan Kumar. P[2], Thirupathi. V[3], Punna Reddy. M[4], Sumanth. K[5], Dr. Venkataramana. B[6]

[1]*Student, BTech CSE(AIML) 4th Year, Holy Mary Inst. Of Tech. and Science, Hyderabad, TG, India,*
[2]*Student, BTech CSE(AIML) 4th Year, Holy Mary Inst. Of Tech. and Science, Hyderabad, TG, India,*
[3]*Student, BTech CSE(AIML) 4th Year, Holy Mary Inst. Of Tech. and Science, Hyderabad, TG, India,*
[4]*Student, BTech CSE(AIML) 4th Year, Holy Mary Inst. Of Tech. and Science, Hyderabad, TG, India,*
[5]*Assoc. prof, CSE(AIML), Holy Mary Inst. Of Tech. and Science, Hyderabad, TG, India,*
[6]*Prof, CSE(AIML), Holy Mary Inst. Of Tech. and Science, Hyderabad, TG, India,*

ABSTRACT:
The project AI-Powered Crop Yield Prediction and Optimization focuses on revolutionizing modern agriculture through Artificial Intelligence (AI) and Machine Learning (ML).The system aims to support farmers and researchers in predicting crop yields with greater accuracy by analyzing key environmental factors such as soil characteristics, rainfall levels, temperature, humidity, and fertilizer application. In an era where traditional agricultural practices struggle to meet rising food demands, the integration of AI and ML provides different methods for analyzing complex environmental data and improving decision-making.The system applies data-driven algorithms like Linear Regression, Random Forest, and Neural Networks to study agricultural data and predict crop productivity with improved accuracy.The platform is developed using HTML, CSS, and JavaScript for the front-end interface, providing an interactive and responsive user experience. The Python Django framework is used for the back-end to handle model processing, prediction logic, and database interaction. MySQL serves as the central data storage system, ensuring efficient management of user and environmental data. By integrating these technologies, the system offers an intelligent webbased platform that modernizes conventional farming practices and promotes a smart agriculture environment.
The system doesn’t just predict crop yields-it also gives useful advice on which crops to grow, how to manage fertilizers, and how to use resources efficiently. By showing real-time data in clear charts and graphs, it helps farmers understand the results and plan their farming activities more effectively. The integration of intelligent AI analytics and an easy-to-use platform helps farmers take informed, proactive actions toward efficient farming and environmental sustainability. This project connects the gap between advanced data analytics and agriculture, highlighting how technology can enhance crop production, optimize resource use, and respond to environmental challenges. Ultimately, the AI-powered system serves as an intelligent, scalable decision-support platform, contributing to sustainable farming, food security, and the modernization of agriculture. Through this seamless combination of artificial intelligence and machine learning. This project stands as a vital step toward the digital transformation of modern agriculture.
KEYWORDS: Machine learning algorithms, Precision Agriculture, Smart farming, Datadriven Decision support, Sustainable farming, Web-based agriculture system

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I. INTRODUCTION:

Agriculture is perhaps the most vital industry for human existence since it supplies food, raw materials, and jobs for millions of individuals globally. But today's farmers have numerous challenges including unpredictable climatic conditions, land degradation, insects, diseases, and water shortages. These issues normally result in low crop yields and financial losses. With the increasing global population, there is a strong need to produce more food efficiently and sustainably. This is where modern technology, especially Artificial Intelligence (AI), plays a major role in transforming traditional farming into smart farming. AI-powered systems can help farmers make better decisions by using data collected from various sources such as satellites, sensors, drones, and weather stations. For instance, AI can evaluate moisture levels in the soil, the level of nutrients, temperatures, and rainfall levels to advise the appropriate time to plant, irrigate, and harvest. It also helps identify plant diseases at an early stage by processing images from cameras or drones, allowing farmers to make swift decisions to avert losses.

One of the key uses of AI in agriculture is **crop yield prediction**. This involves predicting the quantity of crop that is going to be harvested before the harvest. Proper prediction of yield assists farmers in planning their resources, mitigating risks, and making improved marketing decisions. It also assists governments and farming groups in making policies, distributing food, and planning storage. Artificial intelligence models like deep learning and machine learning can analyze complex information from historical yields, soil quality, climatic history, and agricultural practices to develop credible yield predictions.Another important application is **farm yield optimization**, whereby the most effective set of farming practices to achieve high productivity with fewer inputs are determined. AI algorithms can play out various scenarios to recommend the best application of fertilizers, water, and pesticides. Not only does this enhance production but also saves the environment by minimizing waste and pollution. AIpowered precision agriculture makes farmers more precise in managing their fields using data maps to apply the correct amount of resources at the correct place and time.

The application of AI in farming is still on the rise, yet already it has delivered immensely well in enhancing efficiency, sustainability, and profitability. Farmers can transition from an era of guesswork to informed decision-making with the assistance of AI, leading to more stable and predictable crop yields. With technology becoming more affordable and readily available, even small farmers can take advantage of these technologies.Summing up, AI-driven crop yield estimation and optimization are a big leap in agricultural progress. It is a fusion of data strength, algorithms, and automation used to address actual world farming challenges. The technology not only aids farmers in making intelligent choices but also makes contributions to food security across the world and sustainable agricultural expansion in the coming generation.

II. LITERATURE REVIEW:

Recent studies demonstrate how artificial intelligence, machine learning, and deep learning are increasingly being used to forecast crop yields and improve farming methods. Accurate and realtime crop yield forecasting is made possible by methods that combine IoT, remote sensing, and climate data, assisting farmers and policymakers in making well-informed decisions. High predictive accuracy has been demonstrated by models like Random Forest, Decision Trees, LSTMs, CNNs, and hybrid approaches; Explainable AI (XAI) improves feature importance analysis and model interpretability. Data quality, soil heterogeneity, environmental variability, and model generalization across various regions are still issues, though. All things considered, these studies show how AI-driven frameworks can be used to manage crop diseases, maximize resource use, and raise sustainable agricultural productivity. Precision agriculture has used machine learning techniques, such as supervised, unsupervised, reinforcement, and deep learning, to monitor soil health, maximize crop yield, and effectively manage fertilization and irrigation. To increase productivity and decision-making, these methods make use of sizable datasets from sensors, remote sensing, and climate records. Widespread adoption is hampered by issues like poor data quality, interpretability of the model, and low farmer adoption[1] . This study integrates IoT data with machine learning models like LightGBM, Decision Tree, and Random Forest to provide accurate crop yield predictions and recommendations for precision agriculture. The approach effectively leverages real-time environmental data to optimize crop management and resource use. Drawback: The model's performance may be limited by the scope of environmental factors considered, and deeper insights could require more diverse datasets and advanced deep learning techniques[2] . By examining soil, climate, and agricultural data in precision agriculture, the Crop Yield Prediction Algorithm (CYPA) predicts crop yields using IoT techniques and machine learning models such as Decision Tree Regressor, Random Forest Regressor, and Extra Tree Regressor. By modeling how field and environmental factors affect crop growth, it helps farmers and policymakers make well-informed decisions. Although active learning lessens the need for large labeled datasets, the method may still require them. However, adding more varied soil and climate factors could improve prediction accuracy even more [3]. This survey examines several data mining methods used to forecast crop yields, emphasizing how they can be used to examine sizable agricultural datasets in order to spot trends and enhance decision-making. It compares the efficacy of techniques from earlier studies in precision agriculture. The intricacy and unpredictability of agricultural data limit many methods, necessitating additional development to appropriately handle a range of environmental and soil conditions [4]. The capacity of machine learning techniques to handle sizable, intricate remote sensing datasets for better decision-making is highlighted in this review of methods for predicting crop yield and estimating nitrogen status in precision agriculture. ML techniques support reduced environmental impact and optimized nitrogen management while enabling precise and economical predictions. The integration of various sensor data and the requirement for hybrid systems to completely capture non-linear relationships in agricultural environments may limit the efficacy of these methods [5] . In order to help farmers choose crops and prevent disease, this study offers a machine learning framework that combines soil nutrition, meteorological conditions, and historical crop data to forecast crop yield and disease occurrence. It combines decision tree regression for yield estimation, support vector classifiers for disease prediction, and SARIMAX for weather forecasting. The quality and granularity of the input datasets may limit the model's accuracy, and more localized data may be needed for better generalization when expanding it to different regions [6] . In order to increase forecasting accuracy, this study employs high-resolution sensor and satellite/UAV data to systematically analyze deep learning (DL) applications, such as CNNs and LSTMs, for crop yield prediction. It demonstrates how well DL models predict yields for important crops like corn and wheat. Because results can differ across datasets and environmental conditions, the approach may encounter difficulties in data-poor areas and needs to be updated frequently to maintain accuracy [7] . Using climate records and satellite image time-series data, this study uses deep-transfer-learning techniques, such as TrAdaBoost.R2 and domain-adversarial neural networks with BiLSTM, to forecast crop yields. These methods increase the generalizability and accuracy of predictions across a range of climatic zones. The availability of relevant source data determines how effective transfer learning is, and performance may still be constrained in areas with a dearth of high-quality or scarce datasets [8] . In order to maximize irrigation and nutrient management in agriculture, this study examines precision water and fertilizer application technologies that combine cutting-edge sensors, remote sensing, and machine learning. It emphasizes methods for increasing crop yield and resource efficiency, such as variable rate technology, microirrigation, and predictive modeling. Soil heterogeneity and the absence of standardized indices limit the efficacy of these techniques, necessitating additional study for wider, uniform application [9] . This study uses deep neural networks (DNNs) optimized by genetic algorithms to predict sustainable crop yields using climatic and agricultural variables with high accuracy ($R2 = 0.92$). The best crop classification is guided by the interpretation of feature importance using Explainable AI (LIME). The method's applicability in areas with inconsistent or incomplete datasets is limited by the quality and availability of detailed soil and climate data [10] . Using simulated farm-level data on soil, climate, and management, this study examines machine learning models for crop yield prediction, such as Random Forest, neural networks, and regularized linear models. It demonstrates the significance of data partitioning techniques by demonstrating that Random Forest outperformed other models in predicting future yields. Realworld performance may decline further as a result of unaccounted errors in seasonal weather forecasts, even though even the best machine learning models demonstrated only modest improvement over basic baseline predictions [11] . The application of deep learning and remote sensing, specifically CNNs and LSTMs, to crop yield prediction is examined in this review, with a focus on hybrid models and attention mechanisms for increased accuracy. It illustrates how these methods can improve sustainable agriculture and food security. Poor model generalizability, low data quality, and the requirement for more interpretable AI models in agricultural applications are some of the difficulties [12] . This review looks at how to use remote sensing and imaging technologies to predict crop yields under unusual climate conditions using advanced AI techniques like machine learning (ML), deep learning (DL), ensemble learning, and Explainable AI (XAI). The efficiency of algorithms like Random Forest, SVM, ANN, and CNN in managing multidimensional agricultural data is emphasized. Drawbacks include a lack of widespread use of XAI for interpretability, inconsistent data quality, and reliance on sensor and environmental data, which may compromise the accuracy and generalizability of the model [13] . In comparison to conventional machine learning techniques, this study examines deep learning-based methods for crop yield prediction, emphasizing their capacity to examine variables such as crop growth cycles, soil conditions, and rainfall to produce more precise forecasts. It highlights how DL models can increase prediction accuracy for a variety of crops. Cons: Despite advancements, problems with data quality, model generalizability, and making consistently accurate predictions in a range of agricultural settings still exist [14] . The project uses multivariate datasets with numerical and categorical features to predict crop yield and prices in India using machine learning techniques, particularly Polynomial Regression (PR) and Random Forest Algorithm (RFA). In order to improve model accuracy for sustainable farming decisions, the method focuses on data preprocessing, which includes handling missing values, encoding categorical data, and normalizing features. The model's ability to adjust to unanticipated climatic changes or unreported local factors influencing yield and prices may be limited by its reliance on historical and structured datasets [15] .

III. METHODOLOGY:

The methodology for developing the AI-Powered Crop Yield Prediction and Optimization System is a **Data-Driven Machine Learning** approach, combining **environmental, soil, and cropdata** to accurately forecast crop yields and provide actionable recommendations. The system follows a carefully designed workflow that integrates data collection, preprocessing, predictive modeling, and web-based analytics. The goal is to assist farmers and researchers in making informed, realtime decisions for crop management and resource optimization.

This approach emphasizes modularity and scalability, dividing the system into multiple stages: data acquisition, preprocessing, feature engineering, model training, yield prediction, optimization, and visualization. Each module contributes to improving accuracy, efficiency, and usability, ensuring the system is practical for real-world agricultural applications.

Modern machine learning models, including Linear Regression, Random Forest Regressors, and Artificial Neural Networks (ANNs), play a crucial role in capturing complex relationships between soil properties, weather conditions, crop types, and fertilizer usage. These architectures allow the system to not only predict yields but also provide intelligent recommendations for crop selection, fertilizer management, and resource utilization. The system also integrates a web-based interface developed using HTML, CSS, and JavaScript for visualization, while Python Django handles the backend, enabling real-time model processing and database management. By combining AI analytics with interactive dashboards, the platform empowers users to interpret predictions easily and take proactive steps toward efficient, sustainable, and high-yield farming.

3.1 Introduction to the Methodology

The methodology for the AI-Powered Crop Yield Prediction and Optimisation system describes the complete research and development process followed to design, implement, validate, and optimize an intelligent agricultural decision-support model. This chapter provides an in-depth explanation of every step involved—from identifying the problem, collecting and analyzing datasets, preprocessing and transforming the raw data, selecting suitable machine learning and deep learning techniques, building predictive models, optimizing model outputs, integrating domain knowledge from agriculture, and finally deploying the system for real-world usage. The methodology is carefully structured to ensure scientific rigor, operational efficiency, and technological robustness, ensuring that the proposed system works reliably in diverse agricultural environments and provides actionable insights that enhance crop productivity, reduce risk, and support sustainable farming practices.

3.2 Problem Identification and System Objectives

The first step in the methodology involved identifying the key challenges faced in modern agriculture—unpredictable weather, variable soil conditions, inefficient resource usage, pest infestations, and fluctuating crop yields. The project aims to solve these issues using AI-driven prediction and optimisation techniques. The objective-setting stage involved consulting agricultural research papers, government reports, farmer challenges, and expert feedback to define measurable outcomes such as accurate yield forecasting, real-time crop monitoring, actionable recommendations for irrigation and fertilization, and intelligent optimisation of farm resources. This clear problem framing helped determine the exact datasets needed, the architecture of the model, and the evaluation metrics.

3.3 Dataset Acquisition and Integration

The methodology places strong emphasis on multi-source dataset acquisition because highquality data is the backbone of AI-based agricultural systems. Data was collected from historical crop yield datasets, meteorological sources, soil health records, IoT farm sensors, satellite imagery, pest and disease surveillance data, and agricultural management datasets. The datasets were integrated into a unified data warehouse, ensuring consistency, crossreferencing, and compatibility. Integration involved merging time-series weather data with spatial satellite data, correlating soil properties with crop performance, and aligning farm management logs with yield outcomes. This multi-modal data integration allowed the system to capture complex interactions between environmental, biological, and managerial factors.

3.4 Data Preprocessing and Cleaning

Raw agricultural data is often incomplete, noisy, inconsistent, and prone to errors due to manual entry, sensor malfunctions, or environmental disturbances. Therefore, extensive preprocessing was performed. Missing values were addressed using statistical imputation, KNN-based interpolation, and domain-based logical filling.

Outliers were removed or corrected based on agronomic thresholds. Sensor data was smoothed using rolling averages and time-series filters to eliminate spikes. Satellite images were preprocessed using radiometric correction, georeferencing, noise reduction filters, and NDVI extraction. Qualitative data such as farmer notes or field observations were encoded into numerical categories. This stage ensured that the data fed into the model was consistent, structured, highquality, and machine-learning-ready.

3.5Model Design and Algorithm Selection

The model architecture was designed by evaluating multiple machine learning and deep learning algorithms. Traditional algorithms such as Random Forest, Gradient Boosting, XGBoost, CatBoost, and Support Vector Regression were tested for yield prediction. Deep learning approaches, including LSTM for time-series forecasting, CNN for satellite imagebased vegetation analysis, and hybrid models combining spatial and temporal inputs, were explored. The selection of algorithms was based on accuracy, interpretability, computational efficiency, and ability to handle non-linearity in agricultural data. Ensemble learning was also tested to combine strengths of multiple models. For optimisation tasks, techniques such as Genetic Algorithms, Reinforcement Learning, and linear programming were evaluated to provide resource usage recommendations.

3.6 Model Training and Hyperparameter Tuning

Once the models were selected, they were trained using the structured datasets. The training process was carried out using an 80-20 or 70-30 split depending on dataset size, ensuring sufficient data for both training and validation. Cross-validation (k-fold) was employed to avoid bias and prevent overfitting. Hyperparameter tuning was conducted using grid search, Bayesian optimisation, and random search techniques to identify the best-performing parameter combinations. Regularization techniques, dropout layers, batch normalization, and learning rate optimization were used in deep learning models to enhance generalization capabilities. Training performance was monitored using loss functions, accuracy metrics, and validation graphs.

3.7Model Evaluation and Validation

Evaluation was an essential part of the methodology to ensure reliability and practical applicability. Metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), R^2 score, precision, recall, F1-score, and prediction confidence intervals were calculated. The models were validated against real-world yield data, satellite observations, and seasonal performance patterns. Statistical tests and comparative analysis were performed to verify that predictions aligned with agricultural trends. Additional validation involved running the system through simulated stress scenarios (e.g., drought or excessive rainfall) to assess robustness. The best-performing model was selected based on validation accuracy and consistency.

3.8 Optimisation Framework for Decision Support

After yield prediction, an optimisation framework was designed to recommend actions that improve productivity and resource efficiency. This framework uses predicted yield values, soil moisture projections, weather forecasts, and vegetation indices to generate optimal irrigation schedules, fertilizer dosages, pest management strategies, and crop variety selections. Optimisation algorithms evaluate multiple scenarios and provide the best possible strategy with minimum resource usage and maximum expected yield. Reinforcement Learning-based optimisation helped the system learn long-term strategies that adapt to changing field conditions.

3.9 System Architecture and Workflow Design

A modular system architecture was developed to ensure seamless data flow, model processing, and user interaction. The architecture consists of data ingestion modules, preprocessing pipelines, machine learning engines, optimisation modules, visualization dashboards, and API endpoints for external integration. A layered workflow was adopted:

1. Data Collection Layer – gathers multi-source datasets.
2. Data Processing Layer – cleans, transforms, and engineers features.
3. AI/ML Layer – performs yield prediction and image analysis.
4. OptimaisationLayer_recommends best agriculture best practices
5. Interface Layer – displays results to the user with graphs and insights.

This architecture supports scalability, modular updates, and future additions such as disease detection or automated irrigation systems.

IV. IMPLEMENTATION:

4.1 Implementation of Data Sources and Input Components

The system mainly relies on agricultural data rather than physical hardware. The required data includes soil properties (such as pH, moisture, and nutrient levels), weather conditions
(temperature, rainfall, humidity), and crop-related information. These inputs are collected either from publicly available datasets, farmer inputs, or simulated sensor data. Users enter field details through a web-based form developed using HTML and CSS, while JavaScript is used to validate the inputs and ensure data accuracy. This approach removes the need for costly hardware and allows easy access even for small-scale farmers.

4.2 Implementation of Data Collection and Processing

The collected input data is sent from the frontend to the backend using HTTP requests. Before using the data for prediction, preprocessing is performed to improve data quality. This includes handling missing values, removing inconsistencies, and normalizing numerical data.
These steps help ensure reliable predictions and consistent model performance.

4.3 Implementation of Software System

The backend of the system is developed using Python and Django, which manages data handling, business logic, and communication with the AI model. Django REST framework is used to create APIs that connect the frontend with the backend.
The frontend is developed using HTML for structure, CSS for styling, and JavaScript for user interaction and dynamic updates. This user-friendly interface allows farmers to easily enter data and view prediction results without technical knowledge.

4.4 Implementation of Artificial Intelligence Model

Machine learning algorithms such as Linear Regression, Random Forest, and Decision Tree are used for crop yield prediction and optimization. The model is trained using historical agricultural data that includes crop yield records, weather patterns, and soil conditions. The dataset is divided into training and testing sets to evaluate model accuracy. Performance is measured using metrics like accuracy, mean squared error, and prediction reliability. The best-performing model is selected and integrated into the Django backend for real-time prediction.

4.5 Real-Time Prediction and Result Display

Once the system is deployed, real-time user input is processed through the trained AI model. The model predicts the expected crop yield and provides optimization suggestions. The results are displayed on the web interface in a clear and understandable format. Farmers can view predicted yield values, improvement recommendations, and warning messages related to unfavorable conditions. This helps them make informed decisions and improve overall farm productivity.

V. RESULT:

5.1Results of Input Data and Model Response

When different agricultural inputs such as soil type, rainfall, temperature, humidity, and fertilizer usage were provided to the system, the AI model produced distinct prediction outputs Each set of inputs created a unique data pattern that influenced crop yield prediction. The system successfully learned the relationship between environmental conditions and crop productivity.

Conceptual Data Flow Diagram:

Farmer Input Data
(Soil, Weather, Crop)
↓
Preprocessing & Validation
↓
AI Prediction Model
↓
Predicted Crop Yield

5.2Results of Feature Distribution

After preprocessing, important features such as average rainfall, soil moisture level, temperature range, and fertilizer quantity were extracted. These features played a major role in determining crop yield.

Raw Agricultural Data
↓
Data Cleaning & Normalization
↓
Feature Selection
(Soil, Weather, Crop Factors)
↓
Feature Vector

5.3Prediction Accuracy of Machine Learning Models

Multiple machine learning models were trained and tested using historical agricultural data. Among them, Random Forest and Artificial Neural Network (ANN) models produced the most accurate predictions.

Prediction Accuracy Table:

Model Used	**Accuracy (%)**
Linear Regression	85%
Decision Tree	90%
Random Forest	96%
ANN	95%

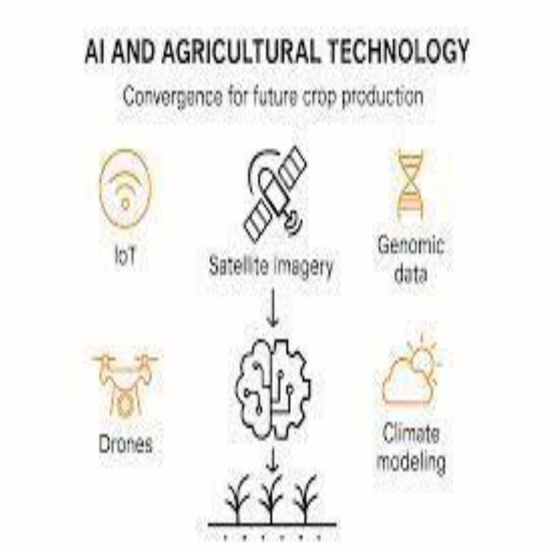
The Random Forest model achieved the highest accuracy due to its ability to handle complex and non-linear agricultural data effectively.

Crop Yield Optimization Results
The system not only predicted yield but also provided optimization suggestions. By analyzing input conditions, the AI model recommended optimal fertilizer usage, irrigation timing, and crop selection.

Optimization Result Diagram:

Current Farming Inputs
↓
AI Analysis
↓
Optimized Recommendations

5.4Real-Time Output Results
The deployed system produced results within **2–3 seconds**, making it suitable for real-time use. The output was displayed in a simple and farmer-friendly format through the web interface.



Output Screen
Crop Name: Rice
Predicted Yield: 4.8 Tons/Hectare
Soil Condition: Suitable
Water Recommendation: Moderate Irrigation
Fertilizer Suggestion: Nitrogen-Based
Alert: Favorable Conditions

VI. CONCLUSION:

This project successfully demonstrates the design and implementation of an **AI-powered crop yield prediction and optimization system** using web technologies and machine learning techniques. By combining historical agricultural data, weather conditions, and soil parameters, the system provides accurate crop yield predictions and meaningful farming recommendations. The use of Artificial Intelligence eliminates traditional guesswork infarming and supports data-driven decision-making.

The results show that machine learning models, especially **Random Forest and Artificial Neural Networks**, perform effectively in predicting crop yield under different environmental conditions. The system is capable of processing real-time inputs and delivering quick results through a user-friendly web interface developed using **HTML, CSS, JavaScript, Python, and Django**.

FUTURE ENHANCEMENT:

The crop yield prediction system can be further improved by integrating **real-time IoT sensors** for collecting live soil moisture, temperature, and humidity data directly from the fields. The accuracy of predictions can be enhanced by applying **deep learning models** such as CNNs and LSTMs for better pattern recognition.

In future versions, the system can be connected to **cloud platforms** to support large-scale data storage and faster processing. A **mobile application** can also be developed to allow farmers to access predictions and recommendations easily from their smartphones. Additionally, satellite imagery and remote sensing data can be incorporated for advanced monitoring of crop health and land conditions.With these enhancements, the system can evolve into a **complete smart agriculture solution** that supports farmers at every stage of the farming process.

REFERENCES:

[1]. Roy, P., Padhiary, M., Hoque, A., Sahu, B., Dey, D., & Kumar, K. (2025). Machine Learning for Precision Agriculture and Crop Yield Optimization: Techniques and Applications. In The Role of Artificial Intelligence in Advancing Applied Life Sciences (pp. 189-233). IGI Global. DOI:10.4018/979-8-3693-9208-9.ch007linkishttps://www.researchgate.net/publication/391307481

[2]. Apat, S.K.; Mishra, J.; Raju, K.S.; Padhy, N. The robust and efficient Machine learning model for smart farming decisions and allied intelligent agriculture decisions. J. Integr. Sci. Technol. 2022, 10, 139–155 https://www.mdpi.com/2624-831X/5/4/28?utm_04

[3]. Talaat, F. M. (2023). Crop yield prediction algorithm (CYPA) in precision agriculture based on IoT techniques and climate changes. Neural Computing & Applications, 35, 17281– 17292. https://doi.org/10.1007/s00521-023-08619-5 Published 30 April 2023.Volume 35, pages 17281–17293

[4]. Beulah, R. (2019). A Survey on Different Data Mining Techniques for Crop Yield Prediction. International Journal of Computer Sciences and Engineering, 7(1), 738–744. https://doi.org/10.26438/ijcse/v7i1.738744

[5]. Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. Computers and Electronics in Agriculture, 151, 61–69. https://www.sciencedirect.com/science/article/abs/pii/S0168169917314710

[6]. Rahman, M. T., "Role of agriculture in Bangladesh economy: uncovering the problems and challenges," International Journal of Business and Management Invention, vol. 6, no. 7, 2017 Saranya, N. & Mythili, A., "Classification of soil and crop suggestion using machine learning techniques," International Journal of Engineering Research & Technology (IJERT), vol. 9, no. 02, pp. 671–673, 2020 https://arxiv.org/html/2403.19273v1?utm

[7]. Abbasi, M., Pishvaee, M. S., Bairamzadeh, S. (2020). Land suitability assessment for Paulownia cultivation using combined GIS and Z-number DEA: A case study. Comput.

[8]. Electron. Agric. 176, 105666. doi: 10.1016/j.compag.2020.105666 https://www.mdpi.com/2227-7080/12/4/43?utm

[9]. Hoffman, L.A.; Etienne, X.L.; Irwin, S.H.; Colino, E.V.; Toasa, J.I. Forecast Performance of WASDE Price Projections for US Corn. Agric. Econ. 2015, 46, 157–171. Sherrick, B.J.;

[10]. Lanoue, C.A.; Woodard, J.; Schnitkey, G.D.; Paulson, N.D. Crop Yield Distributions: Fit, Efficiency, and Performance. Agric. Financ. Rev. 2014, 74, 348–363 https://www.mdpi.com/2072-4292/16/24/4804?utm

[11]. Xing, Y., & Wang, X. (2024). Precise application of water and fertilizer to crops: challenges andopportunities.FrontiersinPlantScience,15, 1444560. https://www.frontiersin.org/journals/plantscience/articles/10.3389/fpls.2024.1444560/full10Malashin, I.; Tynchenko, V.; Gantimurov, A.; Nelyub, V.; Borodulin, A.; Tynchenko, Y. (2024). Predicting Sustainable Crop Yields: Deep Learning and Explainable AI Tools. Sustainability, 16(21), 9437. https://doi.org/10.3390/su16219437

[12]. Abrougui, K., Gabsi, K., Mercatoris, B., Khemis, C., Amami, R., Chahaibi, S. (2019). Prediction of organic potato yield using tillage systems and soil properties by artificial neural network (ANN) and multiple linear regressions (MLR). Soil Tillage Res. 190, 202–208. doi:

[13]. 10.1016/j.still.2019.01.011 Breiman, L. (2001b). Random forests. Mach. Learn. 45, 5–32. doi: 10.1023/A:1010933404324. Hornik, K., Stinchcombe, M., White, H. (1989). Multilayer feedforward networks are universal approximators. Neural Networks 2 (5),359–366. doi:

0.1016/0893-6080(89)90020-8 https://www.frontiersin.org/journals/plant-science/articles/10.3389/fpls.2023.1128388/full

[14]. Jeong, S., Ko, J., Ban, J-O., Shin, T., & Yeom, J-M. (2024). Deep learning-enhanced remote sensing-integrated crop modeling for rice yield prediction. Ecological Informatics, 84, 102886. Tripathi, A., Tiwari, R. K., & Tiwari, S. P. (2022). A deep learning multilayer perceptron and remote sensing approach for soil health-based crop yield estimation. International Journal of Applied Earth Observation and Geoinformation, 113, 102959.Khaki, S., Archontoulis, S. V., & Wang, L. (2020). A CNN-RNN framework for crop yield prediction. Frontiers in Plant Science, 10, 1750. https://www.preprints.org/frontend/manuscript/a3d5c9c11f79f168391d781a275a0f5f/download_pub?utm

[15]. Porter J.R., Semenov M.A. Crop Responses to Climatic Variation. Philosophical Transactions of theRoyalSocietyB:BiologicalSciences.2005;360:2021–2035. doi:10.1098/rstb.2005.1752.

[16]. Tubiello F.N. et al. Crop and pasture response to climate change. Proceedings of the National Academy of Sciences. 2007;104:19686–19691 https://pmc.ncbi.nlm.nih.gov/articles/PMC12473817/

[17]. Kamilaris, A.; PrenafetaBoldú, F. A review on the use of deep learning in agriculture: Focus on crop yield prediction, plant disease detection and weed detection. Comput. Electron. Agric. 2018, 147, 70–90. Bali, A.; Singla, R. A recurrent neural network model for wheat crop yield prediction. Proc. Int. Conf. Data Sci. Mach. Learn. 2019.Elavarasan, D.; Vincent, C.A. A hybrid deep belief network and fuzzy neural network-based model for crop yield prediction. Neural Comput. Appl. 2020, 32, 8685–8698. Khaki, S.; Wang, L. Crop yield prediction using deep neural networks. Front. Plant Sci. 2019, 10, 621.Ren, H.; Zhang, J.; Li, X.; He, M.; Li, T. Hybrid crop yield prediction model combining WOFOST crop simulation and deep learning. Remote Sens. Environ. 2021, 266, 112692.Sun, Q.; Zhu, W.; Wang, Y.; Wang, S. A CNN-LSTM model for county-level soybean yield prediction using multi-source data. Agricultural Systems 2022, 197, 103364 https://www.mdpi.com/2073-4395/14/10/2264?utm

[18]. Bhavani, K. G., & Vani, N. (2025). Artificial Intelligence Driven Crop Price and Yield Prediction Using ML for Sustainable Agriculture. International Journal of Environmental Sciences, 11(3), 734–742. https://doi.org/10.64252/n83byr67