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Research Paper

FUTUREFARM AI: PREDICTIVE ANALYTICS FOR SMART AGRICULTURE USING SENSOR DATA

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ABSTRACT

The main economic activity is agriculture. It is necessary for maintaining the ecosystem. Almost every element of people's life is dependent on a vast range of agricultural products. In addition to responding to climate change, farmers must handle the rising need for more food of higher quality. Farmers must be aware of the weather conditions in order to boost agricultural output and growth because this will allow them to choose the best crop to sow in those conditions. Smart farming powered by IOT improves the entire agricultural system with real-time field monitoring. It displays numerous parameters in crystal-clear real-time, including temperature, humidity, and soil, among others. It is possible to recommend crops by using the right algorithms on sensed data. The project intends to develop a system that predicts agricultural productivity using Internet of Things sensors that collect data on numerous environmental factors, such as temperature, rainfall, and pH. The suggested method seeks to help farmers boost agricultural productivity while decreasing waste and boosting profitability. The project's provision of reliable and timely information about crop yields is one of its primary goals. Farmers now make manual estimates of agricultural production, which can be tedious and imprecise. The proposed system might employ IoT sensors to collect data in real-time, giving farmers precise and current information on crop yields. One of the other objectives of the project is to deal with the unpredictable nature of weather patterns. Weather patterns have become more erratic as a result of climate change, making it difficult for farmers to schedule when to plant and harvest their crops. By examining current practises and adapting them to the current weather patterns, farmers can boost crop yields and decrease waste with the help of the suggested approach. Using machine learning algorithms and environmental data gathered by IoT sensors, the suggested method forecasts crop output. Machine learning algorithms can analyse large datasets and generate precise projections that assist farmers in making decisions. The system can be used by farmers with any degree of technological competency because it is accessible and user-friendly. Farmers may easily access and examine the data collected by the Internet of Things sensors thanks to the user-friendly system interface. Additionally, the system has the ability to provide farmers with immediate feedback, allowing them to alter their agricultural practises in reaction to the current environmental conditions.

Key words: Smart Agriculture, IoT Sensor Data, Deep Autoencoder (DAE), Sensor-Based Crop Monitoring, Environmental Data Analytics, Sustainable Agriculture.

1. INTRODUCTION

The advancement of technology under the Fourth Industrial Revolution (Industry 4.0) is driving the transformation of agriculture into Agriculture 4.0, where traditional farming practices are being enhanced through the integration of Information and Communication Technologies (ICT), the Internet of Things (IoT), Artificial Intelligence (AI), and data analytics. The result of these advancements is real-time insights, automation, and precision-based interventions that have drastically improved agronomy and sustainability throughout farms. Within agricultural systems, Digital Twins (DTs) represent the virtual version of the corresponding farm, where real-time data collected from IoT sensors, Unmanned Aerial Vehicles (UAVs), and remote sensing (RS) technologies are integrated to improve decision-making and productivity. Using machine learning and predictive modeling, DTs allow farmers to monitor, simulate, and optimize farming operations. These systems enhance efficiency and sustainability by providing a continuously updated and interactive virtual model of the farm that exchanges real-time data with its physical counterpart. DTs incorporate IoT sensors, UAVs, RS technologies, and AI-driven analytics to formulate predictive modeling, simulation, and optimization of farming operations. Although successful implementations of DTs are known in other industries, such as manufacturing, aerospace, and healthcare, their use is less developed in this field, where DTs could support decision-making, resource efficiency, and climate adaptation.

Fig 1. Smart Farming with DTs: Connecting Physical and Virtual Farms.

Current research on DTs in agriculture primarily focuses on isolated applications such as irrigation management, disease detection, and crop monitoring, rather than presenting a unified, scalable framework for their deployment. Different studies have addressed IoT, UAVs, machine learning (ML), and remote sensing in smart farming, but the concept of DTs is underdeveloped. This review intends to integrate the recent advances in smart farming technologies while proposing an extensive framework for deploying DTs in precision agriculture. Although previous literature focused on the role of IoT, UAVs, ML, and RS in streamlining farm operations, a systematic integration approach to effectively embed these technologies within a DTs ecosystem is missing.

2. LITERATURE SURVEY

Computer vision enables computers to analyze and interpret visual data, transforming the way plant phenotypes are monitored and evaluated. Convolutional Neural Networks (CNNs) have become integral to computer vision, designed to detect and learn patterns from images [7]. Since the introduction of the groundbreaking CNN model AlexNet [8], which achieved an impressive 99% accuracy in the ImageNet classification challenge, CNNs have become essential tools for image analysis in many domains, including agriculture [9]. Recent developments have seen CNNs used as backbones for many generative AI models based on transformers [10]. In some cases, CNNs have even outperformed well-known transformers [11], which demonstrates that CNNs continue to evolve with new improvements and techniques, making them one of the most reliable computer vision algorithms for tasks such as image classification.

Similarly to other supervised machine learning models, CNNs undergo a training and testing process to learn and evaluate their performance. In the training phase, a CNN model processes a large amount of data through its layers using forward propagation, where it makes predictions [12]. These predictions are compared to true values and the model uses back propagation to adjust its parameters in order to improve its accuracy. After training, the model is evaluated on a separate testing dataset that it has not seen before. During this phase, the model's ability to generalize to new data is tested, as an estimation to real-world performance [13]. Transfer learning can also significantly enhance this process, by allowing CNNs that have been pretrained on large and diverse datasets to leverage this knowledge to improve their performance on datasets specific to agriculture [14,15].

The input data play a crucial role in both training and evaluating models. The quality and diversity of data influences the model's ability to learn and generalize in real-world scenarios with high accuracy [16]. Common types of image data include color images taken by cameras which consist of three channels (red, green, and blue, i.e., RGB) that show scenes the way the human eye would see it. However, images are not limited to the visible light spectrum. They can be captured in various other wavelengths, each providing unique information. For instance, infrared images are captured in the infrared part of the spectrum, radar images use radio waves, multispectral and hyperspectral images capture a wide spectrum of wavelengths across visible and invisible light, and other images can be heatmaps that visually represent data such as temperature or moisture levels. Images can be captured by different types of instruments, such as ground-based sensors embedded in soil or attached to plants to collect in situ data, handheld devices involving digital or multispectral cameras, aerial devices such as Unmanned Aerial Vehicles (UAVs) and satellites, or Unmanned Ground Vehicles (UGVs) [17,18,19,20]. A wide range of data types that are acquired differently exist, each offering a unique insight into various agricultural aspects. The data acquisition instruments also vary significantly, which could enhance the possibilities in agricultural monitoring and management. These advancements present notable research opportunities and have gained significant interest for the last few years. Although numerous reviews have addressed the use of AI in agriculture [21,22,23,24,25,26,27,28,29,30], there is still a lack of comprehensive discussion on data-related aspects and methodologies. This gap in the literature is significant, as effective AI-driven solutions are highly dependent on both data and methodology. To address this gap, we conduct a detailed analysis of recent articles published between 2018 and 2024.

AI in smart agriculture is a multidisciplinary topic that is attracting growing interest from both researchers and engineers. Several recent reviews highlight the advancements and achievements where rapid progress in machine learning made it particularly influential in smart agriculture. For example, Liakos et al. [21] categorized machine learning methods by classifying them based on the issues they addressed. Their review analyzed over 40 studies that they categorized into four areas: crop management, livestock management, soil management, and water management. They concluded that methods such as clustering, decision trees (DTs), regression, neural networks, support vector machines (SVMs), and Bayesian models, are efficient in crop monitoring tasks such as yield prediction, disease detection, weed detection, crop quality, species recognition, tasks related to water, soil, and livestock management.

Kok et al. [22] reviewed the use of SVM in agriculture across the literature. They gathered 60 research articles that used SVM in addition to other machine learning and deep learning models, and then identified which model achieved the best performance. The studies they reviewed covered six key areas of agriculture: nutrient estimation, disease detection, crop classification, yield estimation, quality classification, and weed detection. Their findings indicated that SVM generally performed worse than Random Forest (RF) in certain areas and fell short compared to deep learning methods across all fields.

Kamilaris and Prenafeta-Boldú [23] analyzed 23 studies on how deep learning is used in farming and how methods are evaluated as well as how they compared to other approaches. They also conducted an experiment which goal is to detect missing vegetables in a sugar cane field. By using CNNs, they achieved 79.2% accuracy, which the authors considered low accuracy because of mislabeled images in their dataset.

Kamilaris and Prenafeta-Boldú [24] published a review on deep learning in agriculture, including insights on image preprocessing, image augmentation, and testing. A list of 14 image datasets that are publicly available was also provided.

While some reviews cover a global overview of AI uses in smart agriculture, others focused on more specific use cases. For instance, Liu and Wang [25] presented deep learning methods to detect diseases and pests in plants. Classification methods were detailed along with their advantages and drawbacks. Their findings indicate that some methods such as deep learning, especially CNNs, performed better than others, e.g., K-means, DT, SVM, and K-Nearest Neighbors (KNN). Another list of 14 image datasets of plant diseases and pests was also provided.

Saleem et al. [26] provided a list of studies that use CNNs in smart agriculture, in addition to visualization methods, e.g., segmentation maps, heatmaps, saliency maps, that are useful for analyzing decisions made by machine learning algorithms.

Kamarudin et al. [27] conducted a review on the use of deep learning in topics related to water stress such as evapotranspiration, water stress identification, soil moisture estimation, and soil water modeling. The review showed that deep learning models outperform traditional machine learning approaches in these applications. However, they also highlight that the application of deep learning in plant water stress assessment is still relatively new, and further research is needed to improve models.

3. PROPOSED SYSTEM

The project begins with the acquisition of an agricultural yield dataset containing environmental and historical variables such as temperature, rainfall, humidity, soil pH, and past crop yields, which are crucial for predicting future agricultural productivity. In the data preprocessing phase, the dataset is cleaned by handling missing or null values through imputation or removal, and statistical summaries are generated to understand feature distributions. A Random Forest Regressor (RFR) is first implemented as the baseline model, leveraging its ensemble of decision trees to predict yield and evaluating its performance using MAE, MSE, and R² metrics. As an enhancement, a hybrid model combining a Denoising Autoencoder (DAE) with Gradient Boosting Regressor (GBR) is proposed. The DAE extracts a refined, noise-free representation of the input data, which is then fed into the GBR to perform accurate yield predictions by capturing complex, non-linear patterns. This deep learning and boosting hybrid aims to outperform the baseline by improving generalization and predictive accuracy in agricultural yield forecasting.

Fig 2. Block diagram of proposed system.

After training and evaluating both models—Random Forest Regressor and the proposed DAE + Gradient Boosting Regressor—their performance is compared through a visual performance comparison graph that plots key evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R² score. This comparison helps clearly identify which model offers superior accuracy and reliability for predicting agricultural yields. In the final step, the trained DAE + Gradient Boosting Regressor model is used to make predictions on unseen test data, which undergoes the same preprocessing and feature transformation as the training data, including encoding via the DAE. The model generates yield predictions for each test instance, appends these predictions to the dataset, and displays them for user interpretation. This enables farmers or stakeholders to utilize the system's insights in real-world scenarios, aiding in data-driven agricultural planning and decision-making.

Deep Auto Encoder (DAE) Feature Extraction is highly advantageous for agriculture yield prediction using IoT data. IoT sensors in agriculture often produce high-dimensional, noisy data like soil moisture, temperature, and light intensity, and DAEs can effectively reduce this dimensionality while preserving critical patterns, such as seasonal trends or soil health indicators, which are essential for accurate yield prediction. The use of dropout layers (Dropout(0.3)) in the architecture prevents overfitting, ensuring the model generalizes well to new, unseen data from diverse farming conditions. Additionally, the non-linear relu activations across layers allow the DAE to capture complex, non-linear relationships in the data, such as how temperature and humidity interact to affect crop growth. The reduced learning rate (0.0001) in the Adam optimizer ensures stable training, which is crucial for handling the variability in IoT data, making the DAE a robust tool for precision agriculture.

The Deep Autoencoder (DAE) model begins by accepting high-dimensional IoT data from agricultural sensors—such as soil moisture, temperature, humidity, and rainfall—through an input layer defined by Input(shape=(input_dim,)), where input_dim represents the number of features (e.g., 100). The first encoding layer, Dense(512, activation='relu'), transforms the data into 512 dimensions while learning non-linear patterns, followed by a Dropout(0.3) layer to prevent overfitting. The next layer, Dense(256, activation='relu'), further compresses the data and is again followed by dropout. This is succeeded by the bottleneck layer, Dense(128, activation='relu'), which represents the most compressed and essential feature representation of the input, capturing abstract patterns like soil health or seasonal trends. Decoding begins with Dense(256, activation='relu') and dropout, gradually reconstructing the original input, followed by Dense(512, activation='relu') and finally the output layer Dense(input_dim, activation='linear'), which restores the original feature size. The model is compiled using the Mean Squared Error (MSE) loss function and optimized with the Adam optimizer (learning rate = 0.0001), aiming to minimize reconstruction error. This DAE architecture enables the model to denoise and compress IoT data, enhancing the quality of inputs for downstream tasks like agricultural yield prediction.

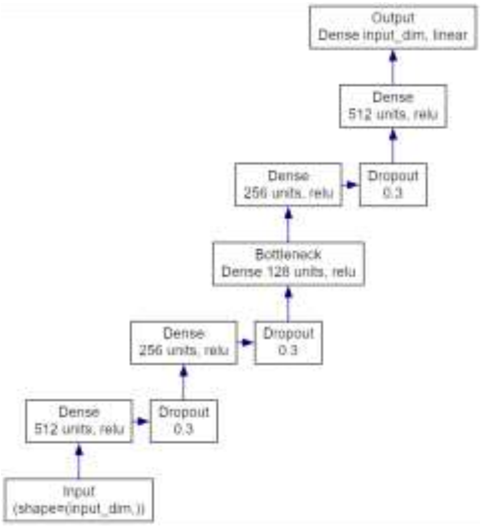

Figure 3. Proposed DAE Flowchart.

Gradient Boosting Regression (GBR), when applied to DAE-extracted features for agriculture yield prediction from IoT data, offers several advantages tailored to this application. GBR excels in modeling complex, non-linear relationships between the compressed DAE features—like latent representations of soil moisture, temperature, and humidity patterns—and the continuous target variable, crop yield. This is critical in agriculture, where yield depends on intricate interactions of environmental factors that DAE features capture. GBR's iterative boosting approach minimizes prediction errors by focusing on difficult-to-predict samples, improving accuracy for diverse farming conditions. Additionally, GBR handles small to medium-sized datasets effectively, which suits IoT data after DAE compression, and provides feature importance scores, helping farmers understand which environmental factors most influence yield, thus supporting better decision-making in precision agriculture.

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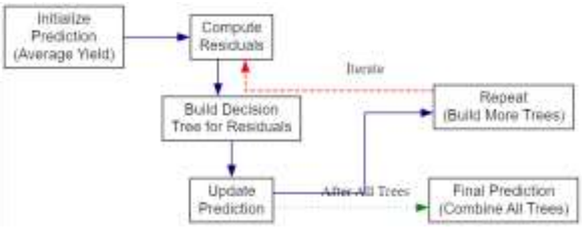

Figure 4. Operation of GBR.

In this advanced stage of the proposed hybrid model, predictions are updated by adding the residuals predicted by each decision tree to the initial prediction, scaled by a learning rate (e.g., 0.1), which ensures small, controlled improvements and prevents overfitting. For instance, if a residual of 4 is predicted and the initial yield estimate is 50, the updated prediction becomes 50.4. This process is repeated iteratively, with each new tree trained on the residuals from the updated predictions, allowing the Gradient Boosting Regressor (GBR) to gradually correct errors and capture complex relationships in the denoised features extracted by the Denoising Autoencoder (DAE). After training all the trees, the final yield prediction is made by aggregating the initial estimate and all tree contributions, effectively capturing non-linear dependencies such as how drought conditions or optimal soil parameters influence crop yield. Once trained, this GBR model can be applied to new sensor-derived DAE features, enabling farmers to predict yield and make informed decisions about irrigation, fertilization, or harvesting. Additionally, the model highlights which features most influence predictions, guiding better resource management. The hybrid DAE + GBR approach offers several advantages: it reduces noise and dimensionality through DAE, improves accuracy through sequential error correction in GBR, handles high-dimensional data efficiently, reduces overfitting, and provides adaptability across various agricultural datasets, making it a powerful tool for real-world yield forecasting.

4. RESULTS

Fig. 5 presents the exploratory data analysis (EDA) plots generated as part of the project. These plots provide an initial understanding of the relationships between various features in the dataset and the target variable (yield per hectare). The visualizations include correlation heatmaps, distribution plots, and scatter plots to identify patterns, trends, and potential outliers in the data. The EDA is essential for uncovering any underlying data issues and ensuring the dataset's suitability for modeling. It helps in visualizing how features such as soil quality, seed variety, and fertilizer amount affect yield and aids in identifying the most relevant features for model training.

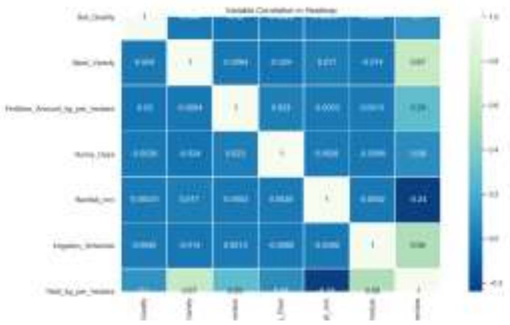

Fig 5. EDA Plots of the Project

Fig. 6 illustrates the data preprocessing stage within the GUI interface. In this step, the system processes the dataset to handle missing values, scale numerical features, and split the data into training and testing sets. The GUI provides an interactive display where users can inspect the preprocessing results, such as the number of missing values for each feature and the distribution of scaled values. The preprocessing phase prepares the data by normalizing numerical values and ensuring consistency before feeding it into the machine learning models. It also includes the splitting of the dataset into training and testing sets, with an 80-20 split, ensuring that the model is evaluated on unseen data.

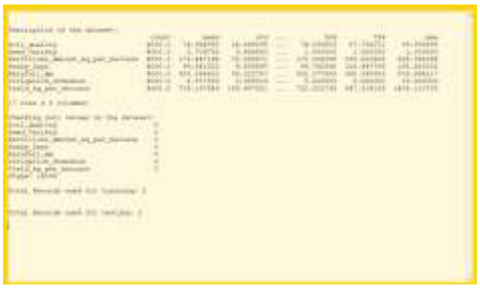

Fig 6. Data Preprocessing in the GUI

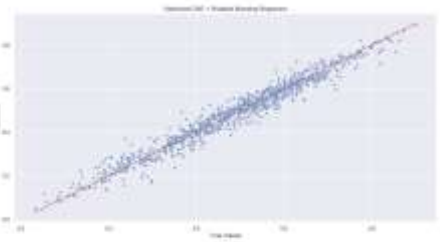

Fig 7. Performance Metrics and Regression Scatter Plot of DAE + Gradient Boosting Regressor Model

Fig 7 shows the performance metrics and regression scatter plot for the Optimized DAE + Gradient Boosting Regressor model. The performance metrics highlight the superior predictive capabilities of this hybrid model compared to the Random Forest Regressor. The MAE is 0.0249, the MSE is 0.0011, the RMSE is 0.0329, and the R² score is 0.9523, indicating a significantly better fit and higher accuracy. The regression scatter plot illustrates the improved predictions of the DAE + Gradient Boosting Regressor model, with the predicted values closely aligning with the actual values. This visual representation emphasizes the enhanced prediction accuracy of the DAE + Gradient Boosting approach.

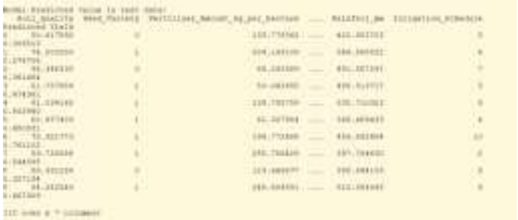

Fig 8. Model Prediction on Test Data

Fig 8 showcases the model's predictions on the test data. After training the machine learning models, the system makes predictions on a separate test dataset that was not used during the training process. The results are displayed within the GUI, allowing users to compare the predicted yield values with the actual values from the test data. The test data contains unseen instances, and the model's ability to predict the yield values accurately is crucial for assessing its generalization capability. This figure highlights the practical application of the model in real-world scenarios, where the model's predictions can inform decision-making processes in agriculture.

Table 1. Model Performance Metrics

Model	MAE	MSE	RMSE	R² Score
Existing Random Forest Regressor	0.0506	0.0040	0.0633	0.8235
Proposed DAE + Gradient Boosting Regressor	0.0249	0.0011	0.0329	0.9523

The table 1 compares the performance metrics of two models for agriculture yield prediction from IoT data: the Random Forest Regressor (Fig. 4) and the Optimized DAE + Gradient Boosting Regressor (Fig. 5), across Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R²) score. The Random Forest Regressor has an MAE of 0.0506, indicating an average prediction error of 0.0506 units, an MSE of 0.0040, an RMSE of 0.0633, and an R² score of 0.8235, meaning it explains 82.35% of the variance in the yield data, reflecting a good but not exceptional fit. In contrast, the Optimized DAE + Gradient Boosting Regressor shows superior performance with an MAE of 0.0249, halving the average error, an MSE of 0.0011, an RMSE of 0.0329, and an R² score of 0.9523, indicating it explains 95.23% of the variance, demonstrating significantly higher accuracy and a better fit to the data. This comparison highlights the hybrid model's enhanced predictive capability, likely due to the DAE's feature extraction improving the Gradient Boosting Regressor's ability to capture complex patterns in the IoT data.

5. CONCLUSION

The research Smart Agriculture Yield Forecaster: AI-based Prediction using IoT Sensor Data aims to develop an AI-powered system capable of accurately predicting crop yield based on various agricultural parameters. By utilizing machine learning algorithms such as Random Forest Regressor and the proposed DAE combined with Gradient Boosting Regressor, the research demonstrates the potential of leveraging both traditional and advanced techniques for agricultural forecasting. The data preprocessing steps, including feature scaling and null value handling, ensure that the input data is prepared in the best possible way to train the models. The performance metrics indicate the effectiveness of the models in predicting crop yield, allowing for actionable insights to be derived for farmers and agricultural stakeholders. The proposed hybrid model, combining DAE with Gradient Boosting Regressor, offers improved performance in yield prediction compared to the traditional Random Forest approach.

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