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Article

Metaverse-Based Precision Agriculture: Integrating IoT, AI, and Data Analytics for Sustainable Development

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Abstract: The fast development of digital technologies has changed the contemporary agriculture, making it more precise, data-driven, and sustainable in managing the farm. Nevertheless, farmers continue to experience difficulties in terms of observing the process of soil dynamics, optimization of irrigation, and real-time visualization of the state of the fields, which results in the inefficiency of resources and the instability of yields. In order to overcome these constraints, the study suggests the implementation of a combined metaverse-based precision agriculture system comprising of IoT sensing, artificial intelligence-enhanced prediction, and advanced data analytics. A 6-in-1 agro sensor has been used to collect real-time soil parameters such as pH, EC, moisture, temperature, phosphorus, and potassium and utilize them in a Raspberry Pi IoT platform. The Karnataka soil moisture dataset is then trained through CNN, LSTM and CNN-LSTM models after cleaning, smoothing and normalization to classify and predict soil moisture. The system is represented in an interactive metaverse system as an immersive system to monitor and make decisions. Based on the experimental results, it is concluded that the hybrid CNN-LSTM model is superior and the RMSE, MAE, MAPE and R2 values are 0.142, 0.810, 27.342 and 0.829 respectively, making it a valuable model for sustainable and accurate irrigation management.
Keywords: Precision agriculture, Artificial Intelligence, deep learning, Soil Monitoring Sensors

1. Introduction

The agricultural sector is in a state of tremendous change due to the many rapid advances in technology, growing pressure from environment, and demand to produce more sustainable food for the rest of the world [1, 2]. Traditional farming, which is essential to the human civilization, is no longer sufficient to cope with the challenges of climate variability, soil degradation, resource scarcity and the need for higher productivity of the plants grown [3]. Digital agriculture technologies have transformed the capacity of farmers to monitor, analyse and manage agricultural ecosystems in recent years, including the use of the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing and advanced data analytics; as shown in Figure 1 [4]. Such technologies open up a new field of activity: agriculture in the metaverse [5]. The metaverse offers new challenges and opportunities for precision agriculture, remote monitoring, predictive modelling and decision making as it enables 3D immersive, interactive and data-rich virtual environments.

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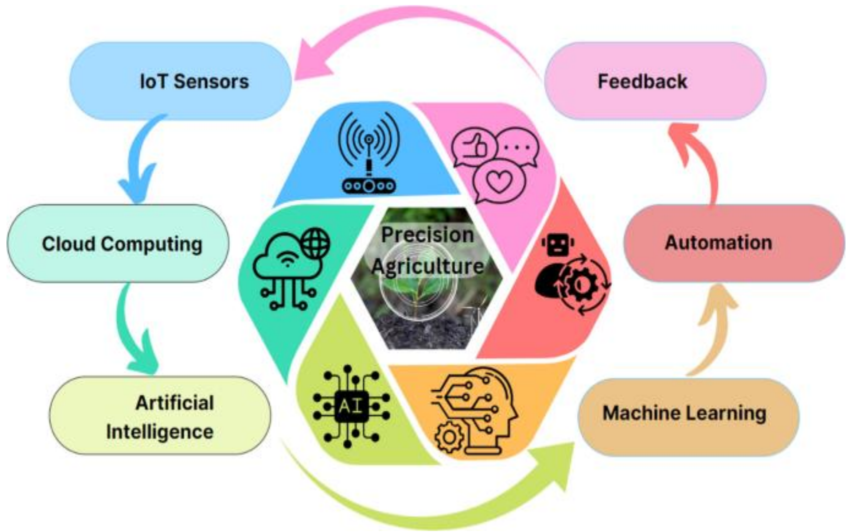

Figure 1: Precision agriculture components [7].

The advent of the metaverse into farming is a paradigm shift from the farm management model of the real world to the mixed real-virtual model [8]. In the model, real-time data from the IoT sensor, such as soil wetness, pH, nutrient, temperature and plant health, is sent into virtual environments on a continuous basis. This enables farmers, scientists and Government officials to view and interact with fields remotely [9]. In figure 2, the smart agriculture IoT sensors are shown. Digital models of farm environment can be developed, allowing parties involved to test in virtual environments and understand how crops respond to this testing or to best manage resources without entering the field. These capabilities help to understand the situation considerably, lower risks during operations and aid in the informed and sustainable decision making process [10].

In this transformation, AI is a key component working with vast amounts of data collected by sensor, drone and satellite networks, including multispectral, temporal and environmental information. Machine learning and deep learning algorithms can accurately model soil dynamics, predict moisture stress, identify nutrient deficiencies and assess yield variations [12]. If these forecasting information is combined with metaverse, it can be shown and rendered three-dimensionally and interactively, allowing stakeholders to understand the information intuitively and take action [13]. A farmer could view the stress patterns across an imaginary farm, test various irrigation alternatives, and predict the outcomes from various harvest scenarios under a range of climate situations. This combination of AI-driven analytics with metaverse visualization allows quicker problem discovery as well as resource efficiency and better sustainability [14].

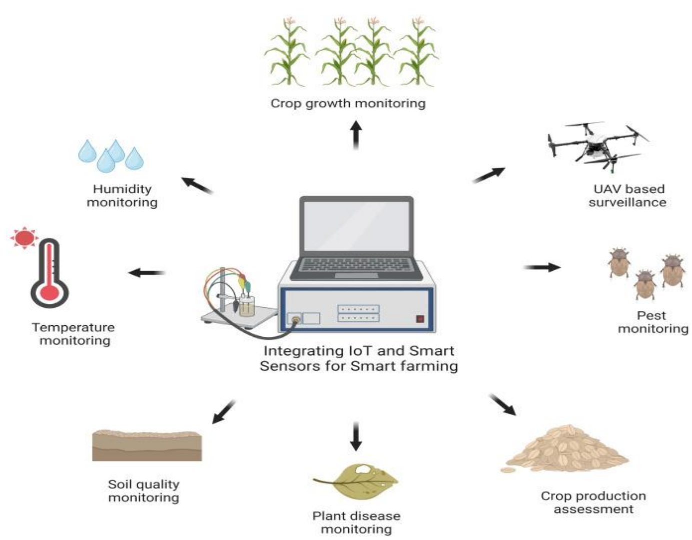

Figure 2: IoT sensor for smart farming [15].

To sum up, the fusion of IoT, AI, and data analytics in the metaverse is a revolutionary and forward-looking structure for green agricultural growth [16]. Driven by these technologies, this interwoven system enables greater farming precision, reduces error risks, and enables eco-friendly farming by using real-time monitoring, intelligent modelling, immersive visualization and collaborative participation [17]. During some of the tougher times in the world, such a radical digital environment can be the solution for a large-scale farm, adaptive and sustainable farming and as a result: food supply in the future[18].

In this study, the researchers suggest a metaverse-based precision agriculture system that integrates the Internet of Things (IoT) sensing, artificial intelligence (AI) modeling, and advanced data analytics for sustainable agriculture. A 6-in-1 agro sensor measures real time soil pH, EC, moisture, temperature, phosphorus and potassium and feeds the retrieved data to a system running on a Raspberry Pi which performs the data analysis for the IoT system. Once data cleaning, smoothing and normalization, CNN, LSTM and hybrid CNN-LSTM models are trained with these data to generate accurate soil moisture predictions. The resulting predictions are made available in a metaverse setting where it facilitates immersive monitoring, decision-making and remote farm management, thus, contributing to resource efficiency and sustainability.

I. To design an IoT-enabled agricultural sensing framework capable of capturing real-time soil parameters such as pH, EC, moisture, temperature, phosphorus, and potassium using a multi-sensor agro module.
II. To preprocess and standardize the collected soil dataset through cleaning, smoothing, noise removal, and normalization to ensure high-quality inputs for predictive modeling.
III. To develop and evaluate AI-based deep learning models—CNN, LSTM, and hybrid CNN-LSTM—for accurate soil-moisture prediction and classification under varying environmental conditions.
IV. To compare model performance using evaluation metrics such as MAPE, RMSE, MAE, and R^2 to identify the most effective predictive model for precision agriculture applications.

2. Literature Survey

The recent developments in the field of precision agriculture illustrate the increased integration of deep learning, IoT, UAV-based sensing, WSNs and machine learning models to enhance crop monitoring, yield prediction, and management of resources. The effectiveness of the UAV-based remote sensing and the detection of palm trees by using YOLO models demonstrated by Hajjaji et al. (2025) [19] showed that the YOLOv8-HighAug performed better with an AP of 0.88. In a similar manner, the TCRM model has been introduced by Singh et al. [20] (2025) and demonstrated to be 94% accurate when a real-time environmental factor is used in conjunction with the cloud platform to provide personalized crop recommendations. Building up remote sensing potential, Guo et al. (2025) [21] introduced CMTNet, a CNN-Transformer model to perform hyperspectral crop classification, with the highest accuracy of 99.58 on three UAV sets. The study by NR et al. (2024) [22] discussed the intersection of the IoT and deep learning to optimize the prediction of irrigation and crop yield, focusing on the real-time sensing and analytics. Meanwhile, Vats et al. (2024) [23] created NeuroRF FarmSense, an IoT-based crop recommendation system that has a NeuroRF classifier with an accuracy of 99.82, which proves the great potential of hybrid NN–RF architectures. The IoT-based pest detection platform proposed by Ahmed et al. (2024) [24] has a recall of 98.92% and mAP of 97.3 and demonstrated the significance of embedded computing and CNN-based features in the real field environments. The comparison of literature survey is presented in table 1.

Table 1: Comparison of literature survey

Author & Year	Technology / Method Used	Dataset / Experimental Setup	Key Results / Performance	Contribution to Precision Agriculture
Hajjaji et al., 2025	UAV-based Remote Sensing, YOLOv5 (6l, L, L-HighAug), YOLOv8-HighAug	Palm tree UAV images	YOLOv8-HighAug: AP = 0.88, Precision = 0.87, Recall = 0.86	Accurate palm tree detection for yield estimation and orchard planning
Singh et al., 2025	TCRM (Machine Learning + Cloud), SMS-based alerts	Real-time environmental & agronomic data	Accuracy = 94%, Precision = 94.46%, Recall = 94%, F1 = 93.97%, 5-fold CV = 97.67%	Personalized crop recommendation system improving sustainability & yield

Guo et al., 2025	CMTNet (CNN + Transformer hybrid) for hyperspectral classification	WHU-Hi-LongKou, WHU-Hi-HanChuan, WHU-Hi-HongHu	OA: 99.58%, 97.29%, 98.31%	High-precision hyperspectral crop classification in complex environments
NR et al., 2024	IoT Sensors + Deep Learning analytics	IoT-based soil, moisture, temp. monitoring	Improved irrigation scheduling, anomaly detection, yield prediction	Integrates IoT + DL for real-time optimization of farm operations
Vats et al., 2024	IoT framework + NeuroRF Classifier (NN + Random Forest hybrid)	Kaggle Crop Dataset (2,200 entries, 7 attributes)	Accuracy = 99.82%	Advanced crop recommendation and prediction for sustainable agriculture
Ahmed et al., 2024	IoT smart insect trap + CNN classifier	1000+ images (fruit fly vs non-fruit fly)	Accuracy = 97.5%, Recall = 98.92%, mAP = 97.3%	Automated pest detection reducing human error and improving crop protection
Pandiyaraju et al., 2023	WSNs + Election-based Aquila Optimizer + Optimized CNN	Sensor network cluster experiments	99.23% accuracy, 98.24% network lifetime, 50% lower energy use	Energy-efficient WSN architecture for monitoring agricultural fields
Senapaty et al., 2023	IoT-enabled nutrient sensing + MSVM-DAG-FFO	Real-time soil NPK, temp., moisture, GPS data	Accuracy = 0.973	Soil nutrient classification + crop recommendation for field decision-making
Abuzanouneh et al., 2022	IoT + ML (AAA-optimized LS-SVM)	Soil moisture, humidity, temperature, light	Accuracy = 0.975	Smart irrigation system for automated water management

One of the main contributions to the field is optimized WSN-based solutions for energy-efficient monitoring. Pandiyaraju et al. (2023) [25] introduced the Election-based Aquila Optimizer with an optimized CNN architecture, which extended the network lifetime and made it possible to achieve an accuracy of 99.23% in agricultural WSN applications. Senapaty et al. (2023) [26] introduced IoTSNA-CR, a cloud-connected IoT model for soil nutrient classification and crop recommendation using MSVM-DAG-FFO, that reached an accuracy of 0.973. Abuzanouneh et al. (2022) [27] created a smart irrigation system (IoTML-SIS) powered by IoT and ML, which integrated AAA-optimized LS-SVM to achieve 0.975 accuracy in irrigation decision-making. On the whole, these studies demonstrate the emergence of a trend toward the use of intelligent, data-driven, and automated systems that, by virtue of their sustainability, precision, and decision-making capabilities, permeate the field of modern agriculture.

3. Research Methodology

Figure 3 depicts an IoT-driven soil assessment and deep-learning classification system for precision agriculture. Various soil-health sensors such as pH, electrical conductivity (EC), phosphorus, potassium, temperature, and moisture are shown on the left, which gather real-time field data. The sensors are combined into a 6-in-1 agro-sensor module that sends the data to a Raspberry Pi which serves as the central processing and communication unit.

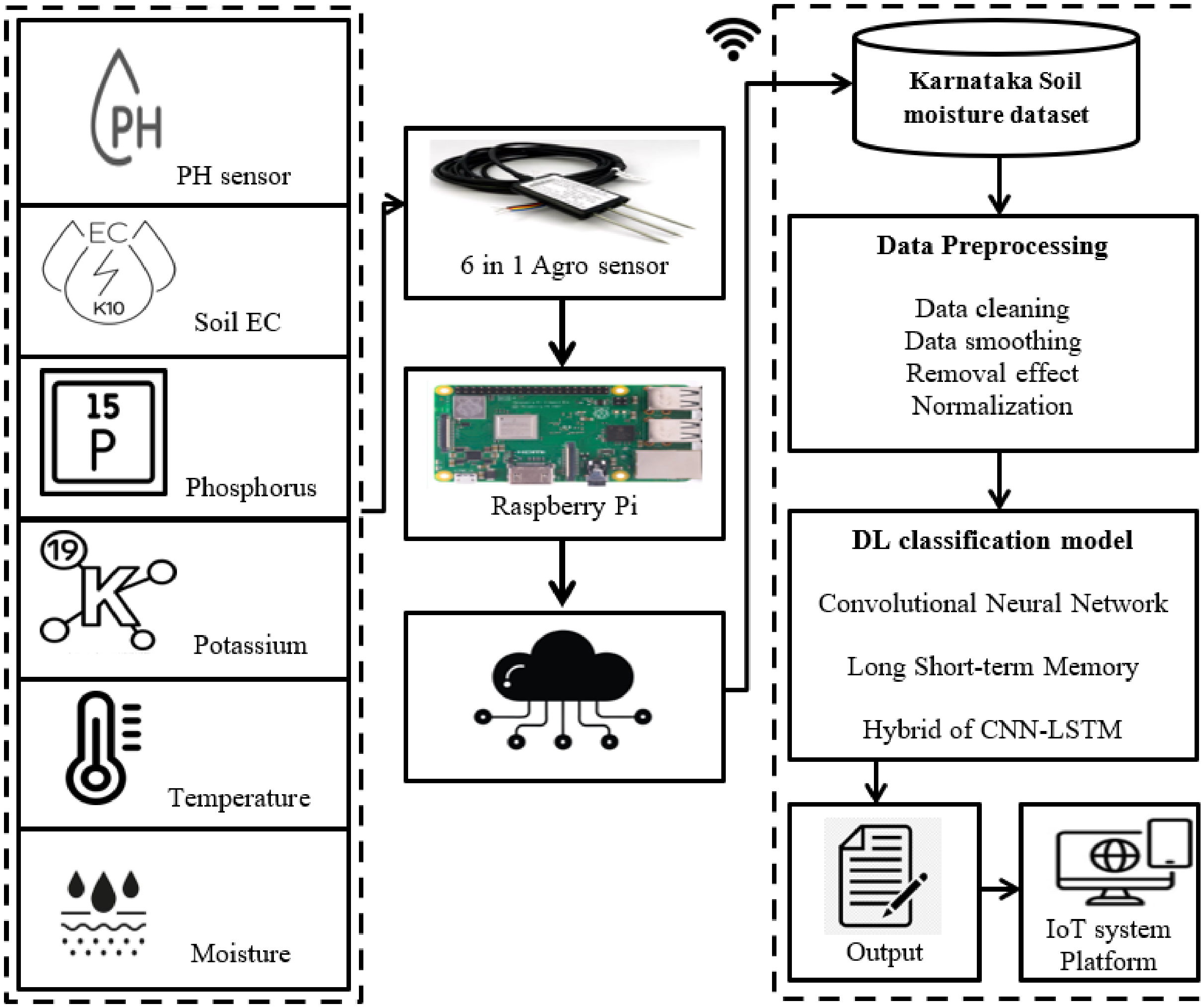

Figure 3: Flowchart of research methodology

The Raspberry Pi sends the sensor data to a cloud platform, where it is merged with an external Karnataka soil-moisture dataset. The data then undergo several preprocessing steps like cleaning, smoothing, removal effect, and normalization to ensure top-quality inputs for model training. The processed dataset is used for deep-learning classification models such as a Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and a hybrid CNN-LSTM model to accurately predict and classify soil moisture. The ultimate outcome is received via an IoT system platform into which they can make decisions in real time in the field.

3.1 Agro Sensors

- pH Sensor

The main factor which determines what nutrients are accessible and how the crops grow is the pH value of the soil, which is measured with a pH sensor. It can help farmers determine whether their soil is acid or limy and in need of some acid or lime. By keeping the pH at a suitable level, the nutrients can be absorbed more efficiently and the general fertility of the soil can be enhanced, thus making it possible to farm in a sustainable way.

- Electrical Conductivity (EC) Sensor

The conductivity of the soil to electric current is measured by an EC sensor to determine the salinity level of the soil. High levels of salinity in the soil can prevent the growth of plants and decrease their ability to absorb water. With EC monitoring, farmers can detect salt build-up in their fields, alter irrigation methods, and keep nutrient concentrations at an appropriate level for healthy crop growth and balanced soil conditions.

- Phosphorus Sensor

The amount of available phosphorus in the soil can be measured by a phosphorus sensor, which is extremely important for the development of the root and for the transfer of energy inside the plant. Good measurement results with this sensor allow one to know if there is not enough or too much nutrient due to fertilization in order to apply fertilizer accurately for effective management of nutrients with less negative impact on the environment improving productivity.

- Potassium Sensor

Potassium sensor determines the potassium content, which is the most important for plant metabolism, water regulation, and disease resistance. Keeping track of potassium levels is the main way plants get the necessary nutrients for a healthy development and they become more resistant to different kinds of stress. Besides, this device is instrumental in enabling precision fertilization, thus not allowing the waste of nutrients, and at the same time, facilitating the unaltered condition of the soil which is necessary for its great performance in agriculture.

- Temperature Sensor

Through a soil temperature sensor, thermal conditions are recorded which affect the germination of seeds, the activity of microbes and nutrient cycling. Monitoring the changes in temperature could help the farmers know when the plants need to be planted and when to start the irrigation. This sensor facilitates enhanced planning in crops, improvement of efficiency in growth, and decision-making in agriculture that is sensitive to temperature.

- Moisture Sensor

A soil moisture sensor is used to measure water content in the soil which can assist farmers in maximizing irrigation. It avoids over watering and under watering and gives real time information on soil hydration. Moisture sensors are useful in increasing water-use efficiency, resource saving, and an adequate supply of moisture to the crops that can grow healthy and give better yield. The proposed work hardware setup is depicted in figure 4.

Figure 4: Hardware Setup of the proposed work

3.2 Processing layer

3.2.1 Dataset Used

The Karnataka soil moisture data [28] is a generalized set of region related soil moisture values collected in different agricultural areas in the state of Karnataka. The dataset records both time and spatial changes in soil moisture that depend on climatic, rainfall conditions, crop production, soil type and irrigation. The field sensors, meteorological stations, and remote sensors provide a high resolution of the dynamics of soil-water, usually measured by field measurement. This information may be critical to assessing drought conditions and to irrigation and precision farming scheduling. Through trends of moisture prediction, in terms of the different districts, the researchers and farmers can have an improved insight on the seasonal changes and predict the areas where moisture is deficient and how to manage the crops.

Table 2: Dataset Sample

pH	Soil EC	Phosphorus	Potassium	Moisture	Temperature	Plant Type	Timestamp
6.021428	0.237700	15.987947	133.206193	79.234006	52.094083	Carrots	2015-04-01
6.342420	0.211844	15.305906	137.856536	75.612889	51.349760	Carrots	2015-05-01
6.684784	0.290343	14.778959	132.994257	77.277833	61.162072	Carrots	2015-06-01
6.552203	0.407055	12.328408	109.766048	76.426754	72.280843	Carrots	2015-07-01
6.705262	0.533824	11.215420	102.429536	76.718368	58.710557	Carrots	2015-08-01

3.2.2 Data Preprocessing

The dataset was preprocessed by addressing duplicate instances and null values. Each numerical feature was given an equal weight during model training by using Min-Max feature scaling to normalize them within the range [0, 1]. In order to make sure that deep learning algorithms could work with the category labels, they used label encoding to turn them into numbers. Figure 5 displays a heatmap of before and after data preprocessing of the employed soil moisture dataset. After performing preprocessing, the highly linear relationships, for example, those between mean_moisture and local_moisture with the correlation coefficient of 0.82, lessen to around 0.41 in their smoothed versions, thus showing that multicollinearity has been reduced. Also, the correlation between moisture and temperature decreases from 0.57 to 0.22. In general, preprocessing stabilizes the relationships between features, reduces the noise, and enhances the data quality for the models that can be used later.

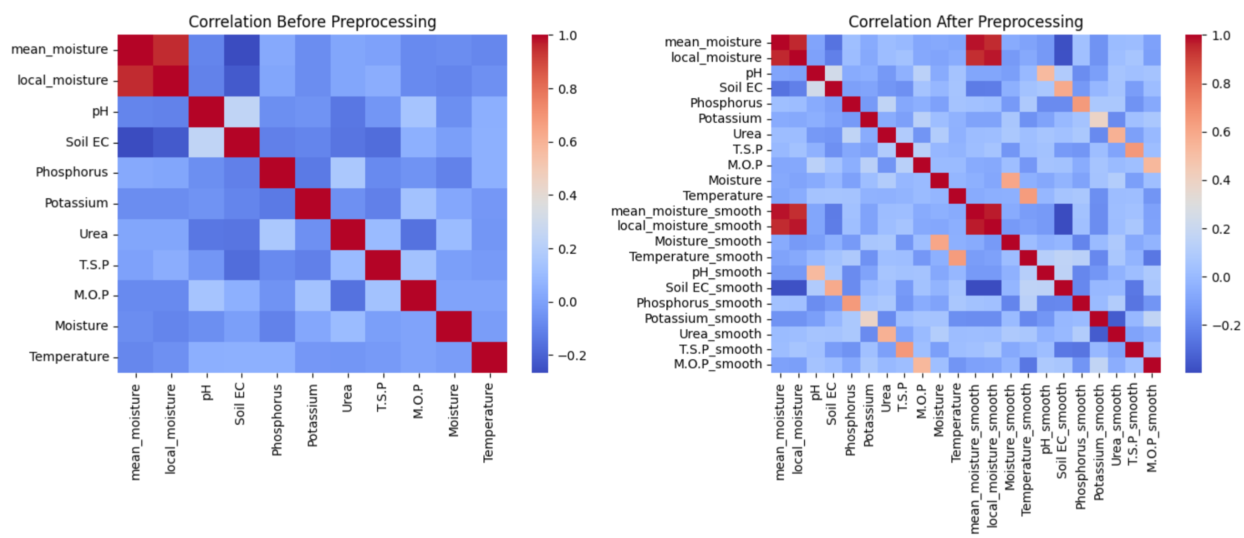

Figure 5: Correlation heat-map before and after preprocessing

The preprocessing visualizations demonstrate the changes to the mean moisture signal that are brought about by cleaning, smoothing, and outlier removal in a stepwise manner. The plots of data preprocessing stages are shown in Figure 6. During the cleaning phase, small inconsistencies like spikes that exceed 12 units or drops that go down to 1.5 units are fixed, thus the cleaned values correspond very closely to the original trend.

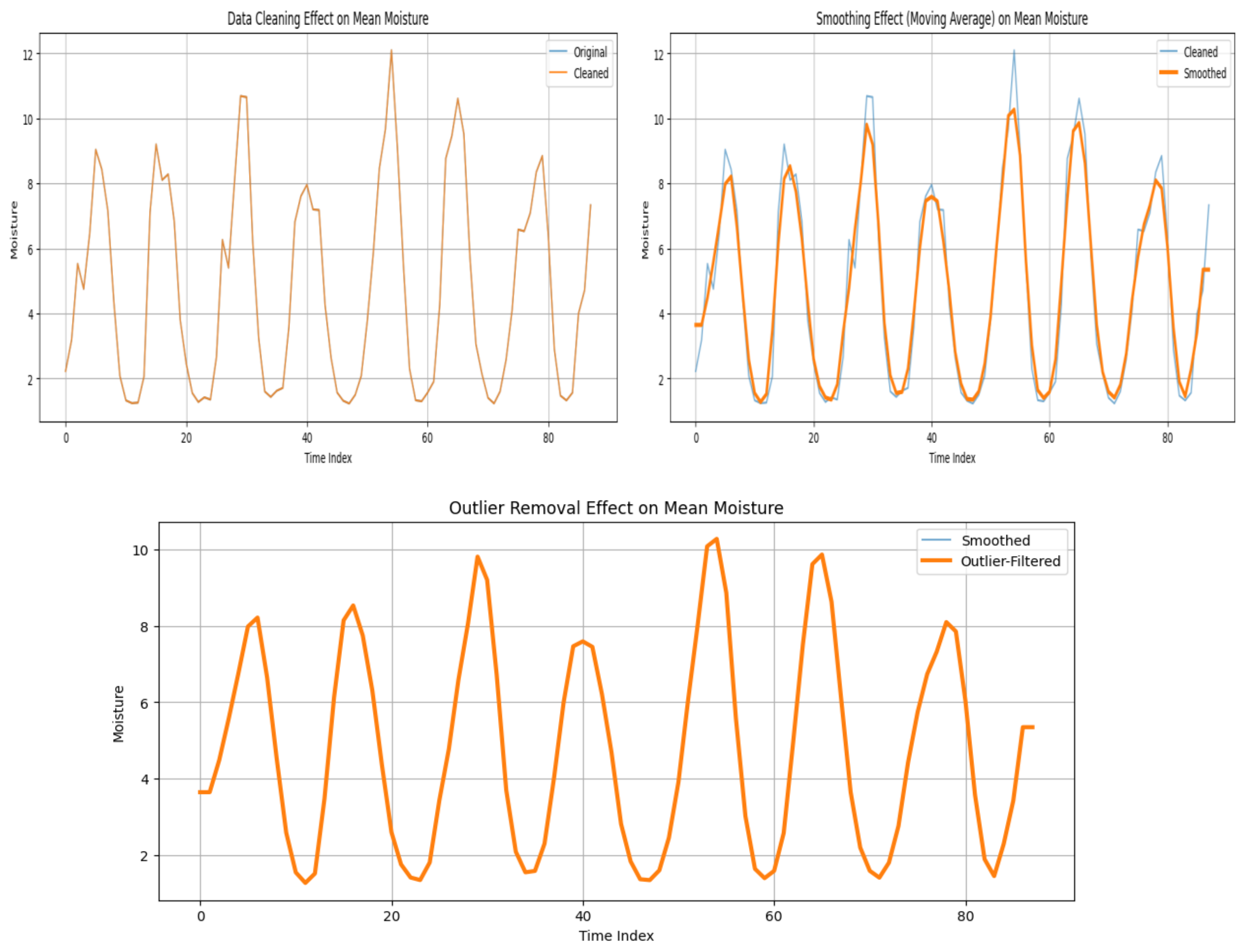

Figure 6: Data preprocessing: Cleaning, b) Smoothing, and c) Removal effect

Moving average smoothing reduces the magnitude of the short-term fluctuations and moves the higher values of the signal up from around 12.3 to near 10.8 and raises the lower values to around 2.5, thereby making the signal function more regularly in an oscillatory manner. The outlier removal procedure is another operation that affects the signal, eliminating odd noise, and most moisture values are still in the 2-10 range. All these processes make data reliable and consistent and helps in reducing the noise, thereby leading to a uniform time series and thus help in predictions related to agriculture using deep learning.

3.2.3 DL Classification Model

- **Convolutional Neural Network**

Deep learning algorithms like convolutional neural networks (CNNs) use a combination of pooling layers, fully connected layers, and several convolutional layers [29]. The visual brain of animals serves as the basis for this multi-layer neural network [30]. CNNs find prevalence in image processing and recognition applications. Multiple computer vision research have employed CNNs for a variety of tasks, including medical image analysis, text and video processing, speech recognition, picture segmentation, object identification, and image categorization [31]. Convolutional, pooling, and fully connected layers are the usual components of CNN architecture [32]. The architecture of convolutional neural networks (CNNs) is shown in Figure 7, and the layers are described briefly:

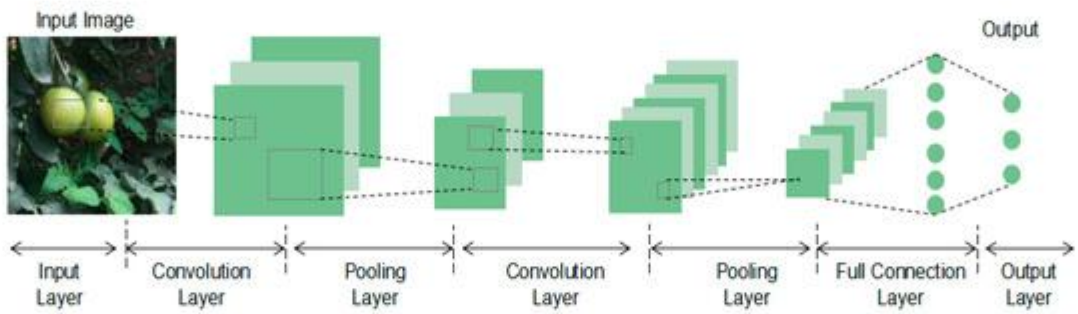

Figure 7: CNN architecture [33].

Convolution layer: The convolution layer uses convolution procedures to gather local training data properties [34]. The activation function takes as input the data and weight parameters from the inputs, together with the offset value; result is the input of the activation function. The relevance of the parameters specified in the CNN determines the size of the output feature graph. Convolution can be calculated using the formula:

$$x_{ij}^{(l)} = f\left(\sum_{m=0}^{k}\sum_{n=0}^{k} x_{i=m,j+n}^{(l-1)} w_{mn}^{(l)} + b^{(l)}\right)$$

Here we have the variables that make up the convolution kernel: k for length or width, w for weight vector, b for bias, and f for activation function. The picture pixel is represented by x.

Pooling layer: Pooling is accomplished by repositioning the sliding window on the feature graph, which is analogous to the idea behind convolution operations [35]. With each step size-dependent movement on the feature map, the presentation value of the region could be retrieved. It was possible to shrink the feature map after pooling procedures. Here is the formula for calculating the pooling operation:

$$x^t = R(\beta^t . P(x^{t-1}) + b^t)$$

In this context, R denotes the activation function, P stands for the pooling function, β denotes the weight coefficient, and b the bias.

Fully connected layer: CNNs fully connected layer is located at its very end. The two-dimensional feature map is transformed into a one-dimensional vector using the fully connected mode. Afterwards, the vector is mapped to the sample space according to various tasks [36]. To accomplish the final classification or regression task, the input data is mapped to the feature representation space by the convolution and pooling layers that came before it. Then, the fully connected layer takes the feature representation space and maps it to the sample's label space [37].

- **Long Short-Term Memory (LSTM)**

LSTMs are a Recurrent Neural Network (RNN) type. Hochreiter and Schmidhuber [38] suggest it as a solution to the issues of gradient vanishing and long-term reliance. Typically, LSTM cell contains four gates: an input, an output, a forget, and a cell state. Figure 8 below shows the structure of an LSTM cell.

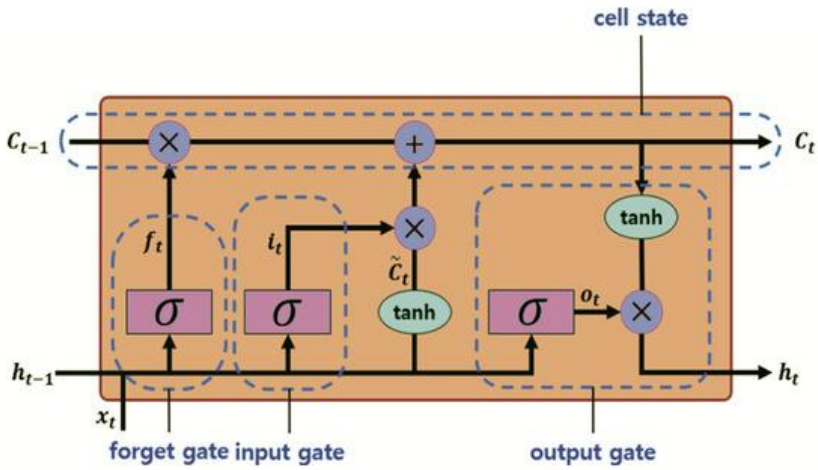

Figure 8: LSTM cell [39].

The following functions are used to calculate h_t, which is the hidden state at time t, for every component in the input sequence, as illustrated in Figure 8.

$$i_t = \sigma(W^i x_t + U^i h_{t-1} + b^i)$$

$$f_t = \sigma(W^f x_t + U^f h_{t-1} + b^f)$$

$$\tilde{C}_t = \tanh(W^{\tilde{C}xt} + U^{\tilde{C}h_{t-1}} + b^{\tilde{C}})$$

$$o_t = \sigma(W_o x_t + U^o h^{t-1} + b^o)$$

$$c_t = \tilde{C}_t \cdot i_t + c_{t-1} \cdot f_t$$

$$h_t = o_t \cdot tanhc_t$$

where h_t is the hidden state at time t, c_t is the cell state at time t, x_t is the input at time t, h_{t-1} is the hidden state at time $t-1$ or the initial hidden state, and $i_t, f_t, \tilde{C}_t, o_t$ are the input, forget, cell, and output gates, respectively. σ is the sigmoid function and $\cdot$ denotes element-wise matrix multiplication.

LSTM networks specialize in handling time series data, whether it's for classification, processing, or prediction purposes [40]. The efficacy of LSTM in handling price series has been proven in several studies pertaining to agricultural price prediction. Hence, researchers in this study choose to pursue this line of inquiry by processing price series using an LSTM network.

- **Hybrid Model**

The DL model's ensemble is a common method for improving performance by merging many classifiers. Dataset accuracy could be enhanced by the use of ensemble techniques, which integrate the results of many classifier models [41]. The ensemble frameworks use the two ML models—CNN and LSTM—that were already mentioned because they improve the performance of ML-based classifiers and get better results in agriculture. Figure 9 shows the architecture of hybrid model.

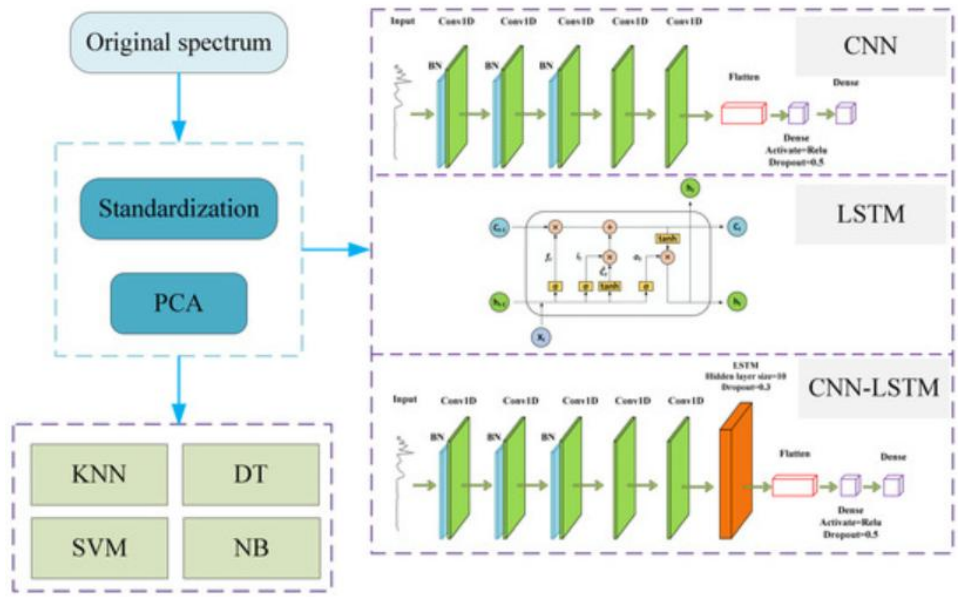

Figure 9: Hybrid of CNN-LSTM [42]

They calculate each models output, $Y_j, (j = 1,2,3, \ldots, m = 6) \in \mathbb{R}^C$ considering C=2 and confidence value $P_i \in \mathbb{R}(i = 1,2)$ on the unrevealed test data where $P_i \in [0,1]$ and $\sum_{i=1}^{C} P_i = 1$. This study presents an approach that utilizes equations to accomplish weighted aggregate of several ML algorithms.

$$P_i^{en} = \frac{\sum_{j=1}^{m=6}(W_i \times P_{ij})}{\sum_{i=1}^{C=2}\sum_{j=1}^{m=6}(W_i \times P_{ij})} \tag{12}$$

The weight of the associated j^{th} classifiers' AUC is denoted as W_j. The output of the ensemble model, $Y \in \mathbb{R}^C$ includes the confidence values $P_i^{en} \in [0,1]$. If $P_i^{en} = \max(Y(X))$, then C_i would be the final class label for the suggested datasets unobserved test data, $X \in \mathbb{R}$, as determined by the ensemble framework [43-46].

3.2.4 Performance Metrics

The evaluation parameters for the prediction model are as follows:

$$Water\ Savings\ (\%) = \frac{Water\ used\ (traditional) - Water\ used\ (optimized)}{Water\ used\ (traditional)} \times 100$$

$$Fertilizer\ Reduction\ (\%) = \frac{Fertlizer\ applied\ (traditional) - Fertlizer\ applied\ (optimized)}{Fertlizer\ applied\ (traditional)} \times 100$$

$$Yield\ increases\ (\%) = \frac{Yield\ (optimized) - Yield\ (traditional)}{Yield\ (traditional)} \times 100$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(x_i - y_i)|$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - y_i}{y_i}\right| \times 100\%$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

4. Result and Analysis

Utilizing Python, the data on soil moisture, temperature, PH, and nutrients was processed to remove outliers, perform cleaning and smoothing operations. The CNN, LSTM and Hybrid models were used for predictive analysis and Matplotlib and Seaborn were used for visualisation and correlation analysis, plotting. Performance metrics were calculated and custom scripts were created to help with precision farming decision making

4.1 Actual vs Predicted moisture of the proposed model

The numerical comparisons of LSTM, CNN and Hybrid CNN-LSTM models in predicting soil moisture as shown in Figure 10-12 indicate how individual models would be in agreement with real sensor measurements in a metaverse-enabled precision agriculture setup. Actual moisture in the LSTM -plot is 1.4 to 5.4, whereas predicted moisture is 1.3 to 4.5 with a consistent underestimation of higher moisture values. In the case of test index 4, the actual value is 5.4, but LSTM predicts 3.4, with a deviation value of 2.0 units.

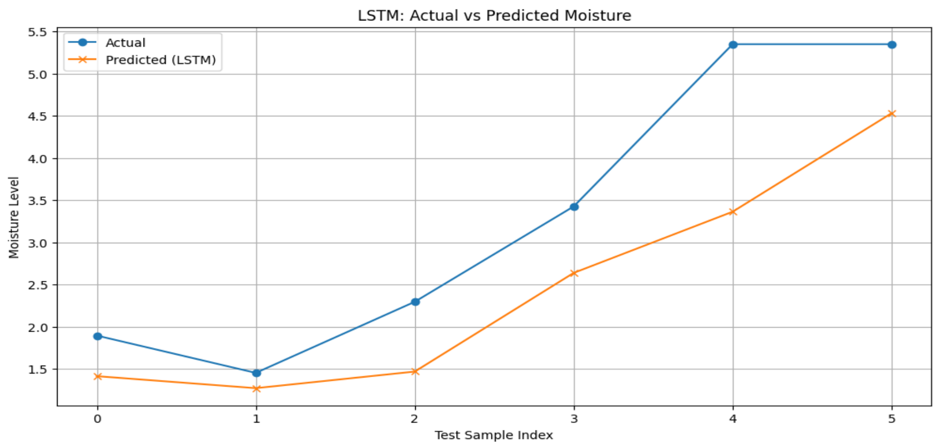

Figure 9: LSTM: Actual vs Predicted moisture

The CNN plot takes care of 18 samples with the actual moisture being the highest point (8.2 index/8) with the predicted CNN being only 5.8 and the difference between the actual and the predicted is being 2.4 units. Nevertheless, CNN estimates on indices 4-10 are very close to the actual increasing trend making the error less than 0.7 units in certain points.

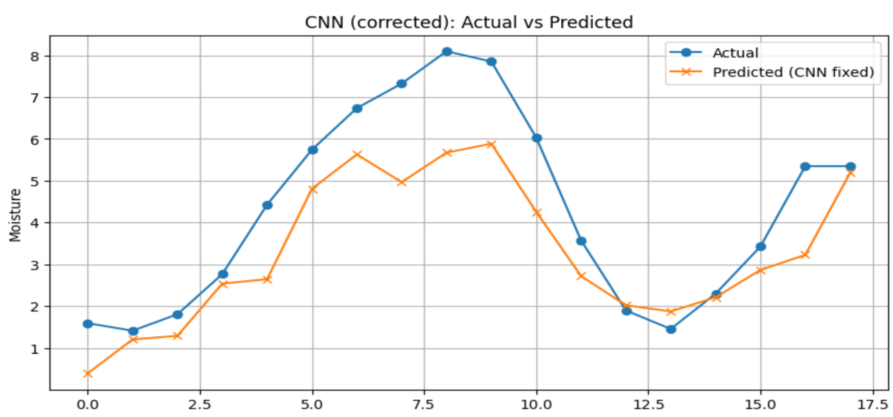

Figure 10: CNN: Actual vs Predicted moisture

The highest alignment is in the Hybrid CNN-LSTM plot which is between 1.4 and 8.1 actual moisture and between 2.6 and 7.1 predicted moisture. The highest index (8) indicates that the actual moisture is 8.1 and the hybrid model predicts 7.1 which is much smaller than LSTM and CNN. All in all, the hybrid model has significant numerical performance indicating that it is more accurate in capturing moisture dynamics.

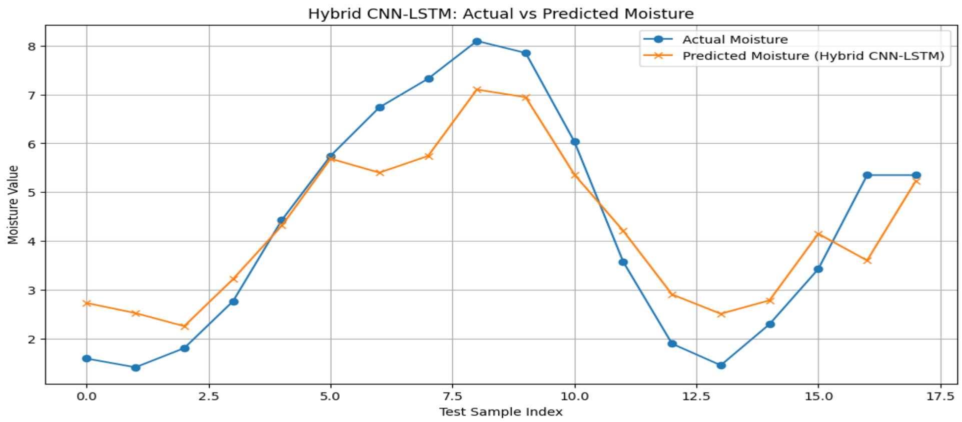

Figure 11: Actual vs Predicted moisture of the hybrid model

4.2 Residual Plot of Proposed Model

The residual plots for LSTM, CNN, and Hybrid CNN–LSTM models serve as a numerical guide to the prediction errors in moisture estimation for metaverse-based precision agriculture, as depicted in Figures 12–14. In the case of the LSTM model, residuals vary between 0.18 and 2.0, which points to a situation of consistent under-prediction. As an example, the residual reaches 2.0 when the predicted moisture is 3.4, thereby indicating that the actual value is quite a bit higher. Low predicted values like 1.3 are associated with residuals in the range of 0.2–0.5, thus they still represent a situation of systematical underestimation.

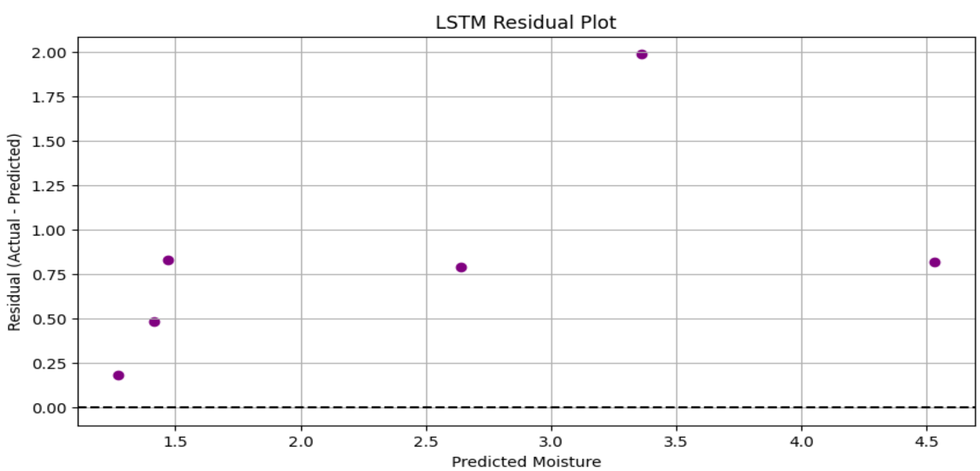

Figure 12: LSTM residual plot

In the CNN residual plot, residuals change more broadly, from -0.40 to 2.40, which shows that both over prediction and under prediction have occurred. A residual of -0.40 is obtained from a predicted moisture of around 2.0, which implies that the model overestimates slightly. At a higher prediction of 5.8, a residual of 2.40 is reached that indicates an appreciable under prediction.

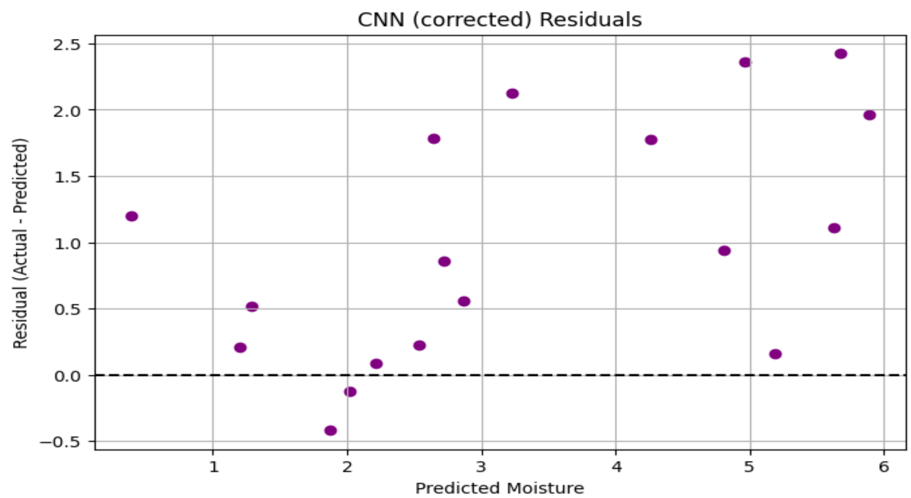

Figure 13: CNN residual plot

Conversely, Hybrid CNNLSTM model has more balanced errors with a residual of between -1.10 and 1.70. The cases of mild over prediction are exhibited by negative residuals, which are -1.10 at predictions of around 2.6. Nonetheless, the predicted values are even at higher levels, such as 7.1, the residual is only 1.0, which is less deviation than among the other models. In general, the hybrid model has a narrower distribution of residual, which means that it has better error stability and predictive accuracy.

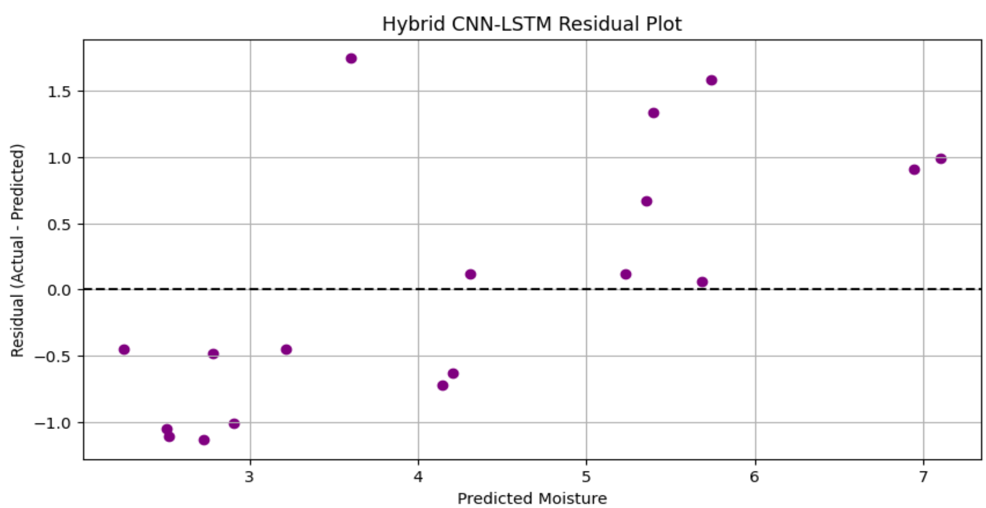

Figure 14: Residual Plot of hybrid Model

4.3 Error Distribution of Proposed Models

The plots of the error distributions (Figure 15, 16 and 17) of the models of LSTM and CNN can help to understand the variability and the magnitude of the errors made in the prediction of the soil moisture. The error in prediction by LSTM model is between 0.20 and 2.00 with the majority of the errors being between 0.50 and 0.90 that is there is a uniform underprediction. The distribution is narrowly spread indicating moderate stability but low accuracy at high levels of moisture.

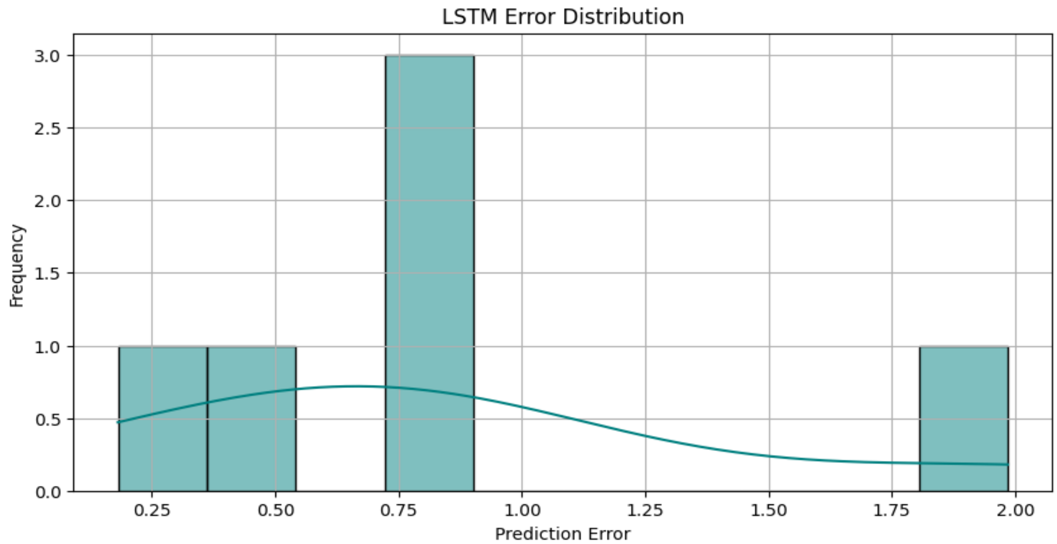

Figure 15: LSTM error distribution

The CNN model shows a wider range of errors between −0.40 and 2.40, meaning that it includes both over predictions and under predictions. Errors close to 0.00 to 0.50 are more often reported, thus better approximation in mid-range moisture conditions can be assumed. However, the larger positive errors above 1.50 indicate CNN struggles with peak moisture values. The broader range of CNN's distribution indicates greater variability than that of LSTM, but the fact that it can compensate for negative deviations shows that it is more flexible.

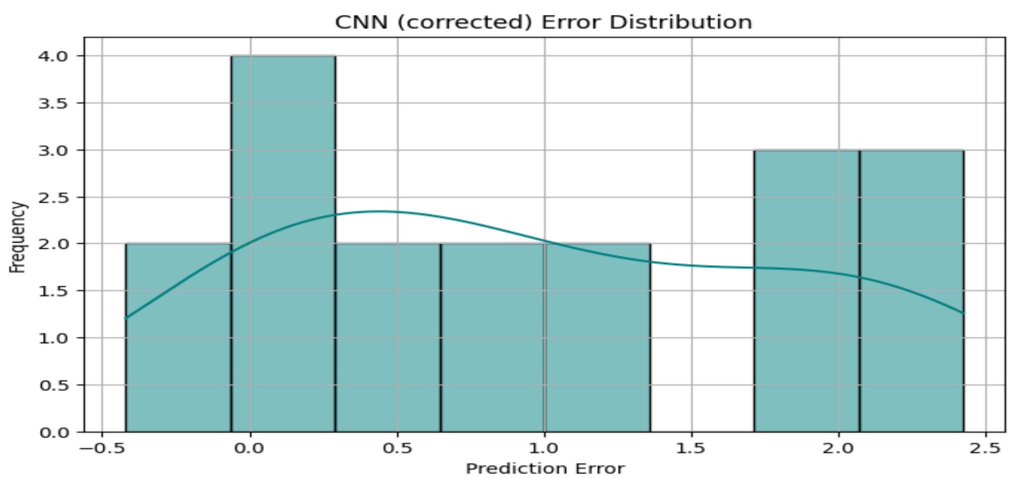

Figure 16: CNN error distribution

On the other hand, the Hybrid CNN-LSTM model shows a steady performance pattern, with most of its prediction errors lying between –1.0 and 0.5. The highest frequency of errors is found in the range from –0.8 to –0.5, which means that the model outputs are slightly underestimated. There are few positive errors—less than one and a half—but they do not happen very often; when they do occur, they can be as large as 1.6. The errors are mostly in this small range, not exceeding 70%, confirming the predictability of the data and its suitability for supporting data-driven agricultural monitoring and decision making.

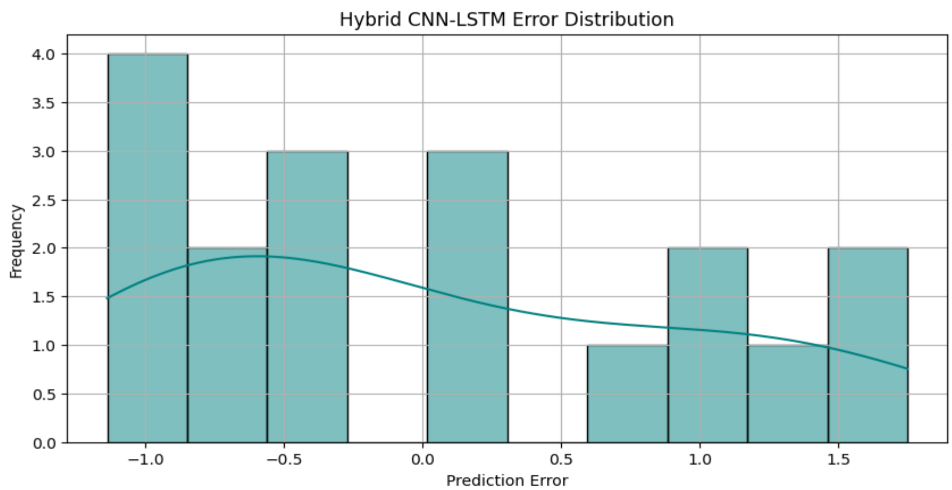

Figure 17: Error Distribution of hybrid Models

4.4 Evaluation of Performance Metrics

The comparison of LSTM, CNN, and Hybrid models underscores the value of combining AI tools that boost the precision of predictions in simulated farming settings, particularly within the Metaverse-based Precision Agriculture context. The Hybrid model has the least RMSE (0.938) and MAE (0.810), which shows that it has high accuracy when modelling real-time inputs of IoT sensors into decision systems that operate in the metaverse. The assessment value of proposed model in terms of performance measures is given in Table 3.

Table 3: Evaluation of proposed model based on performance metrics

Model	RMSE	MAE	MAPE (%)	R^2 Score
LSTM	1.014	0.844	24.873	0.582
CNN	1.318	1.046	24.382	0.662
Hybrid	0.938	0.810	27.342	0.829

It also has a high R 2 score of 0.829, which reflects a high model-data fit needed in sustainable resource planning. Although the LSTM model is moderate with the RMSE of 1.014, the CNN model has higher error rates but still has the lowest MAPE (24.382%) indicating the consistency of predicting using percentages. Figure 18 presents a graph of comparison of proposed model. On the whole, the findings indicate that Hybrid AI models are much more effective in precision agriculture in a scenario of immersive meta-version analytics.

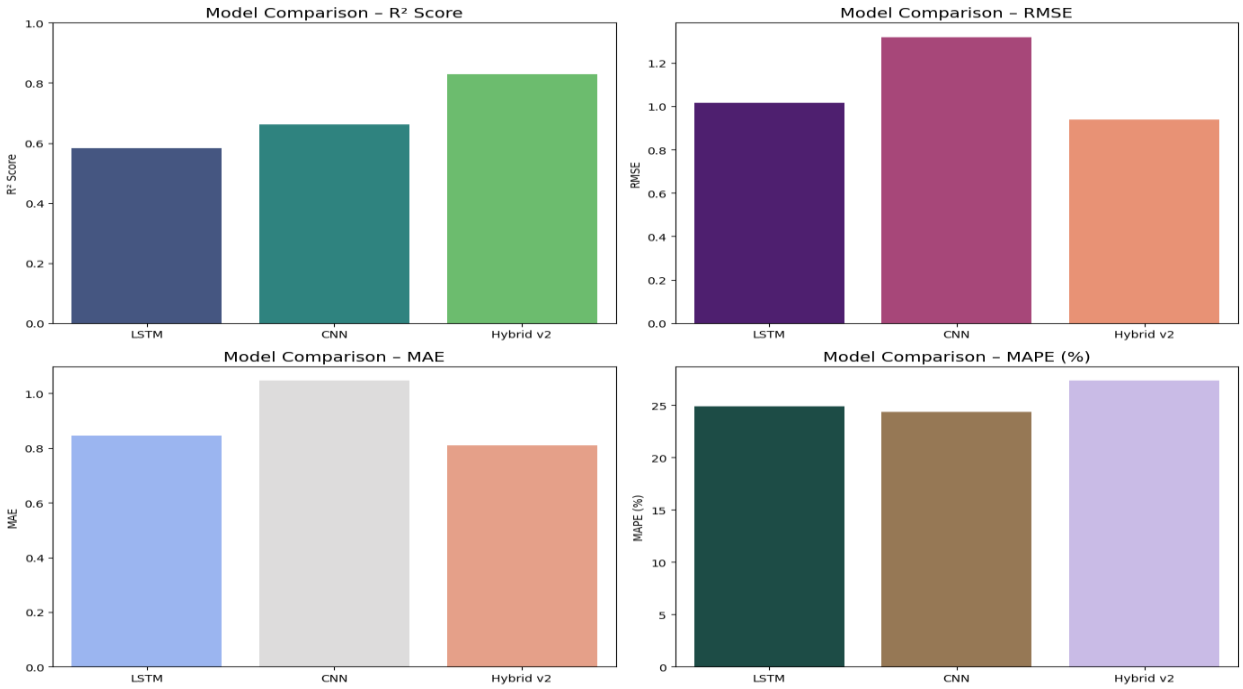

Figure 18: Comparison graph of proposed model

Figure 19 shows the performance of four alternative methods of agricultural optimization Traditional, LSTM, CNN and Hybrid v2, on four parameters, which are very important: water use, fertilizer requirements, crop yield, and water-saving efficiency. The most significant change in the consumption of water is provided by the first subplot, with Traditional methods, which need 1000L of water, and Hybrid v2, which needs 650L, the highest improvement. Further on, fertilizer optimization also shows a depreciation of 50 kg in Traditional to 33 kg in Hybrid v2 showing a better control of nutrients.

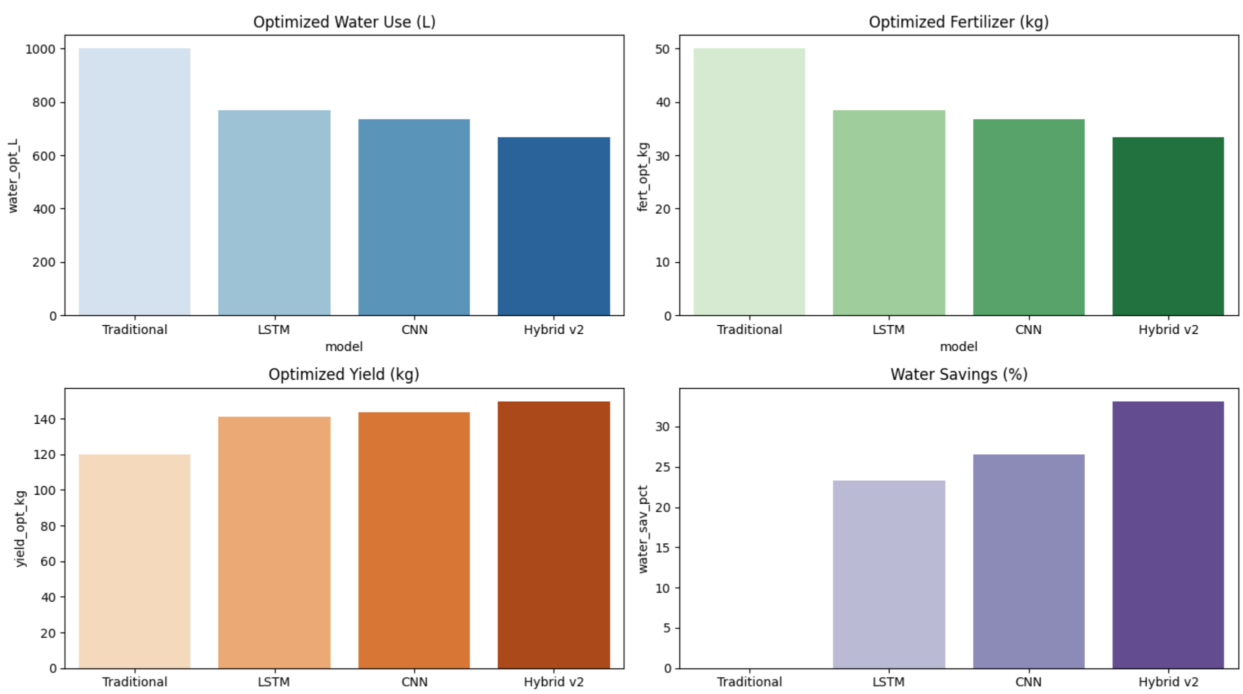

Figure 19: Performance comparison of agricultural models showing optimized water use, fertilizer reduction, yield improvement, and water-saving efficiency

The optimized yield plot shows sustained yield improvement with Traditional generating 120 kg and Hybrid v2 generating 150 kg, which is a good output efficiency. Finally, the water-saving subplot shows that the conservation benefits are significant with Hybrid v2 making the highest saving of 33, and Traditional methods making no savings. In sum, it is important to note that Hybrid v2 has always excelled in terms of minimizing inputs and maximizing productivity.

5. Conclusion

The study indicated a high degree of feasibility for an IoT-based metaverse agricultural system in precision farming as well as sustainable resource management. Real-time soil monitoring sensors such as soil moisture, pH, EC, temperature, phosphorus, and potassium levels working under a networked system with the Raspberry Pi IoT platform allow data collection that can be analyzed on the cloud. The data cleaning smoothing and outlier removal are the processes of pre-processing the data to give reliable and accurate datasets applicable to predictive modeling. A dataset of soil moisture was created for Karnataka, using which deep learning models such as CNN, LSTM and hybrid ensemble were trained and implemented to predict soil moisture and nutrient requirement for crops. This hybrid model was the best, with an RMSE of 0.938, a MAE of 0.810 and an R2 of 0.829, showing that it has a higher predictive capability. In total offered framework is a very strong solution which can help in precision farming more resource efficient, less damaging for environment and able to achieve maximum crop yield based on the data.

Overall, the study highlights the potential of integrated, high-tech sensing, AI modelling and virtual visualization for the future of agriculture. Further studies may include: scaling the system to larger farms, studying climate prediction, and incorporating multi-crop options to better understand precision farming and decision support.

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