A Hybrid Convolutional Neural Network-Temporal Attention Mechanism Approach for Real-Time Prediction of Soil Moisture and Temperature in Precision Agriculture

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***Abstract*—Precision Agriculture is a combination of Artificial Intelligence (AI) and the Internet of Things (IoT) to improve farming efficiency, sustainability, and overall productivity. This work presents hybrid CNN-TAM (Convolutional Neural Network–Temporal Attention Mechanism) model running on Edge AI devices for real time crop soil temperature and Soil Moisture prognosis. IoT sensors gather long term environmental data which is preprocessed to remove noise and extract meaningful spatial and temporal features. CNN can obtain spatial patterns and TAM assigns dynamic attention weights to important time steps enhancing prediction accuracy. The proposed hybrid model surpasses the conventional methods like Linear Regression, Random Forest, LSTM, and independent CNN with the lowest RMSE (1.7). Different from cloud-based deployments, the Edge AI deployment offers reduced latency, consumes lower bandwidth, and is better suited for scalability, enabling large-scale, real-time precision farming. Experimental outcome confirms enhanced real-time prediction capability allowing farmers to optimize irrigation schedules, reduce resource waste, and improve crop resilience against extreme weather conditions. This ensures sustainable resource management, conserves water and fertilizers, and enhances decision-making in agriculture. The results demonstrate the capability of AI-driven decision-support tools in present-day agriculture and presents a scalable, cost-effective and deployable solution for both small- and large-scale farms. By emphasizing data privacy, real-time processing, and low-latency inference, this research contributes to the area of precision agriculture relying on AI, addressing key challenges such as real-time analytics, unreliable connectivity, and the need for immediate on-site decision-making. The study develops an AI-powered system for intelligent farm management to support sustainable and Smart Irrigation Optimization is used for efficient agricultural practices.**

Keywords*—Precision agriculture; edge AI; convolutional neural network; temporal attention mechanism; smart irrigation optimization

I. Introduction

In the recent history, PA has been a new way of farming that relies on the use of highly developed technologies such as IoT and AI in a bid to improve productivity, conserve resources from wastage, and promote sustainable farming. The integration of Edge AI with precision agriculture is highly crucial since it provides on-location and real-time processing of data that are collected using an array of IoT sensors in farms, facilitating real-time decision-making [1]. The transfer of technology may significantly boost yields, better handle soil health management, and help improve weather prediction for more knowledgeable farm operation. Among the critical parameters that influence agricultural productivity are weather patterns and soil conditions, and they have a direct bearing on crop growth, water consumption, and resource utilization. The use of Temporal Attention Mechanisms with CNNs is a viable solution. CNNs initially designed to process images can be used to restructure data from diverse sources such as soil sensors, satellite images, and drones and capture spatial features such as temperature, moisture in the soil, and nutrients. CNNs or Temporal Attention Mechanisms enable the model to navigate through sensor readings in time-series format and weather patterns and identify dynamic temporal patterns that affect agronomic conditions such as temperature variation, rain pattern, and change in moisture over time [2]. With the combination of spatial as well as temporal data, the hybrid model is able to make enhanced and consistent predictions, providing real-time data about soil status and weather required for efficient crop management [3].

The study seeks to utilize this hybrid method to enhance crop monitoring and intelligent farm management, enabling farmers to maximize the utilization of resources such as water, fertilizers, and pesticides. Real-time weather prediction and soil monitoring via IoT-based Edge AI would allow farmers to make decisions and act in a timely manner to avoid crop diseases, pests, and nutrient deficiencies, thereby maximizing crop yields and minimizing costs [4]. The relevance of this study stems from its ability to solve precision farming challenges by creating AI models that can run directly on edge devices like agricultural sensors or drones with minimal dependency on cloud computing infrastructure. This both lessens the bandwidth load and enhances scalability, making the solution available even in remote agricultural areas where cloud-based systems would be impracticable. Additionally, data processing on the edge keeps sensitive data like weather conditions and soil types safe, leading to improved privacy and regulation compliance [5] Regarding resource optimization, the instant feedback from the system would enable farmers to change irrigation timetables, use fertilizers only where needed, and reduce the effect of weather occurrences like drought or excessive rain [6]. Detection of pests or diseases at an early stage, along with accurate predictions of weather and soil conditions, would allow farmers to act preventively, lessening the necessity for the use of pesticides and enhancing crop health [7]. The hybrid approach, by analysing spatial as well as temporal data, improves the system's accuracy and responsiveness, making agricultural practices more sustainable [8].

The system's ability to deliver real-time prediction and anticipatory control has the potential to greatly enhance the crops' tolerance towards environmental stress, thereby ensuring greater yields and decreased farm losses. The paper further discusses measuring the practicable feasibility of employing a hybrid AI model like that described here for managing intelligent farms in terms of its ability to adapt to heterogeneous forms of data sources as well as provide actionability explainability that is accessible for farmers lacking in technical skill sets. The primary objective is to create an affordable, scalable, and deployable solution for farmers of all sizes, from smallholder farms to large-scale agricultural operations. In addition, the research aims to further the general goals of environmental sustainability by ensuring water and fertilizer loss reduction, minimizing the use of pesticides, and enhancing the overall efficiency of farms [9].Through the implementation of edge-based real-time AI predictive systems, this approach intends to increase the sensitivity of agriculture to changing climatic conditions and lower its carbon footprint. Secondly, the research hopes to encourage broader uses of IoT-based AI technology across the agricultural sector, showcasing their potential to improve productivity, enhance decision-making procedures, and facilitate sustainable agricultural production globally. By focusing on CNNs and Temporal Attention Mechanisms, this study aims to fill the gap that exists in existing systems that rely primarily on static data models or cloud computing and create a more dynamic, responsive, and efficient system for agriculture [10]. The study also investigates the practicability of applying the model to existing agricultural systems, making them compatible with existing infrastructure and enhancing the overall system reliability. The study is part of the global agenda to embrace AI and IoT technology in agriculture since they can reshape the art of agriculture in the face of burgeoning dangers such as climate change, water shortages, and food demands. The outcome of the research will not just encourage precision farming but also enhance sustainable farming practice required to secure future food supplies. By employing an Edge AI-based hybrid technique, this work can revolutionize agriculture by enhancing productivity, decreasing costs, and making agriculture climate-resilient, eventually establishing smart, sustainable agriculture globally [11]. The key contribution of the study is followed as below:

- This study proposes a CNN-TAM model to achieve real soil moisture and temperature prediction for enhanced precision agriculture.
- The fusion of CNN and TAM improves the accuracy of prediction, surpasses traditional models in both RMSE-based evaluation.
- Use of model on Edge AI device decreases latency, reduce bandwidth consumption and enabling real time decision making in farming.
- The suggested method makes irrigation scheduling better, lessens resource loss, and improves sustainability in contemporary agriculture.

The remainder of the paper is organized as follows: Section II provides a review of pertinent work. In Section III, the problem statement is explained. The proposed method is described in Section IV. Section V presents and compares the experimental results. Section VI concludes the work and offers suggestions for additional research.

II. LITERATURE REVIEW

Sharma and Shivandu [10] explain the ways IoT and AI are transforming precision agriculture through automatic monitoring and management of crops. The study identifies the technologies of high-throughput phenotyping, remote sensing, and AgroBots which enable harvesting, sorting, and weed identification to be carried out with increased efficiency and reduced labor and environmental costs. High-throughput phenotyping integrates spectral imaging, robotics, and remote sensing to enhance decision-making related to pest control, fertilization, and irrigation. DGPS and remote sensing offer precise real-time data for soil and crop health assessment, and image segmentation algorithms allow fruit and plant detection under challenging circumstances. PACMAN SCRI for apple orchard management and Project PANTHEON's SCADA system for hazelnut plantations are examples of AI-IoT integration in agriculture. Research gaps, such as scalability to small farms, real-time decision-making, and robustness of AI models, are also covered in the paper. Upcoming advancements such as 5G and 6G cellular networks are projected to push the adoption further. Satisfying data convergence, privacy, and security issues will promote precision agriculture to deliver sustainable and efficient agricultural practice.

Fuentes-Peñailillo [11] address the role of digital agriculture in smart crop management, focusing on IoT, remote sensing, and AI in enhancing crop productivity and sustainability. The article points out how real-time information from IoT and sensor networks can evaluate soil health, plant water status, pest infestation, and environmental conditions. Such information facilitates data-driven decisions to optimize irrigation, fertilization, and pest management. UAVs and drones improve monitoring by performing in-depth field surveys and monitoring crop growth with great accuracy. The research also investigates the application of big data analytics and AI in handling large datasets to detect patterns and trends and provide insights for improved agricultural management. Challenges include low adoption rates due to the complexity of technology, high prices, and farmer training requirements. The research promotes ongoing research and cooperation to break these barriers and facilitate the global implementation of smart agriculture, especially in climate change and resource-scarce regions.

Avalekar et al. [12] discuss the intersection of AI and IoT in agricultural automation systems, their integration with wireless sensor networks and cloud computing. The paper suggests an architecture composed of modules such as Wireless Sensor Networks (WSN), Data Processing and Edge Computing, Cloud Computing, AI and Machine Learning, IoT Integration, and User Interface Control. The study is intended to improve crop quality, optimize yields, embrace weather-sensitive management, and AI-enabled crop rotation. The research hypotheses are AI-controlled quality, embracing real-time weather data inputs, and analytics-based decision-making. AI and IoT will automatically revolutionize precision agriculture on a large scale by optimizing the use of resources and making agriculture more sustainable, the study contends. Paradigm-breaking synergy of AI-IoT-cloud computing is making for a sustainable and effective data-driven agricultural framework. Future research has to defeat connectivity, security of data, and scalability issues of infrastructure if it has to be universally embraced.

Khan, Hassan, and Shahriyar [13] also suggest an IoT- and cloud-based platform for the improvement of onion crop management. The system is IoT sensor-based for online temperature, humidity, and soil moisture measurement supported by aerial drones for remote monitoring. The information is processed on edge computing to reduce latency and securely transmitted to a cloud platform to store and analyze. Applications based on machine learning learn patterns of onion growth, health, and weather conditions and give predictive suggestions on the need for irrigation and fertilization. A dashboard provides farmers an easy way to look at real-time data, and automated alerts inform them about deviations from ideal conditions. Predictive analytics also help plan in the long term by detecting growth patterns. Security measures such as encrypted data storage and transfer safeguard farmer data. The study indicates that cloud and IoT technology enhance the sustainability and productivity of crops but with issues related to cost, scalability, and access in small-scale farming.

Boahen and Choudhary [14] discuss computer vision and AI technologies for precision agriculture, for instance, intelligent monitoring of soil and crops. The article provides developments in machine learning and image processing that enhance the efficiency of resource utilization and crop production. Computer vision provides means for plant health monitoring by autonomous means through spectral analysis for disease detection, nutrient deficiency, and pest attack. Machine learning algorithms improve precision in such analysis to facilitate real-time suggestions on best farming practices. The article directs towards the functions of image segmentation and deep learning in solving variables in illumination as well as backgrounds that are very complex in instances of field deployment. The use of AI-fueled decision support systems allows farmers to attempt precision irrigation, fertilization, and crop management. The article recommends additional research to further fine-tune AI models for various agricultural settings and enhance small-scale farmer adoption.

Soultane, Salih-Alj, and Et-taibi [12] provide an intelligent agriculture system that employs recurrent neural networks (RNN) and edge computing to improve agricultural productivity. The platform employs IoT drones with multispectral cameras and LiDAR to gather large amounts of data on crop health, soil health, and weather conditions IoT sensors like pH, soil moisture, temperature, and humidity sensors provide real-time data for data-driven decision-making. Integration of the RNN model offers predictive analysis to enhance irrigation schedules, monitor possible disease states, and predict crop yields the study highlights the benefits of AI-driven analytics in improving crop yields, reducing resource consumption, and minimizing environmental footprints. But it identifies challenges such as the cost of deployment, the need for skilled personnel, and data privacy concerns that require additional researches and technology improvements.

III. Problem Statement

Precision agriculture is evolving through the integration of AI and IoT, but internal issues such as high implementation costs, limited scalability, data security concerns, and difficulties in real-time decision-making are hampering scale up of the technology adoption. Small farmers lack access to sophisticated digital options, which holds them back from maximizing resource utilization and improving crop yields [13]. Connection problems and computational delay, further hamper real-time decision-making, ultimately reducing the efficiency of AI models under varying environmental conditions. Although AI-based systems significantly improve soil monitoring, irrigation and pest control, challenges such as data privacy concerns, infrastructure latency and model degradation hinder large-scale implementation. Addressing these issues is crucial to to fully harness the AI-IoT synergy for sustainable and intelligent agriculture [14]. This research presents an Edge AI-based CNN-TAM model to tackle these challenges by enabling a real-time, low-latency soil and crop sensing, thereby optimizing farming operations.

IV. Research Methodology

The proposed methodology Fig. 1 illustrates a CNN-TAM (Convolutional Neural Network with Temporal Attention Mechanism) model designed for precision agriculture. The workflow begins with data collection, where IoT sensors gather soil moisture and temperature readings from multiple depths over a decade. Next, data preprocessing ensures quality through cleaning, handling missing values, and outlier removal. Feature engineering extracts spatial and temporal patterns, with CNN identifying spatial dependencies and TAM assigning dynamic attention weights to critical time steps, such as extreme weather events. The CNN architecture involves convolutional layers for feature extraction, ReLU activation for non-linearity, pooling layers for dimensionality reduction, and fully connected layers for classification or regression.

The Temporal Attention Mechanism (TAM) prioritizes key time steps that significantly impact soil moisture and crop health. The CNN-TAM model is deployed on Edge AI devices, enabling real-time analysis and decision-making with minimal latency. Finally, the system undergoes training and validation, ensuring robust prediction accuracy, outperforming traditional models like Linear Regression, Random Forest, LSTM, and standalone CNN in RMSE-based evaluations.

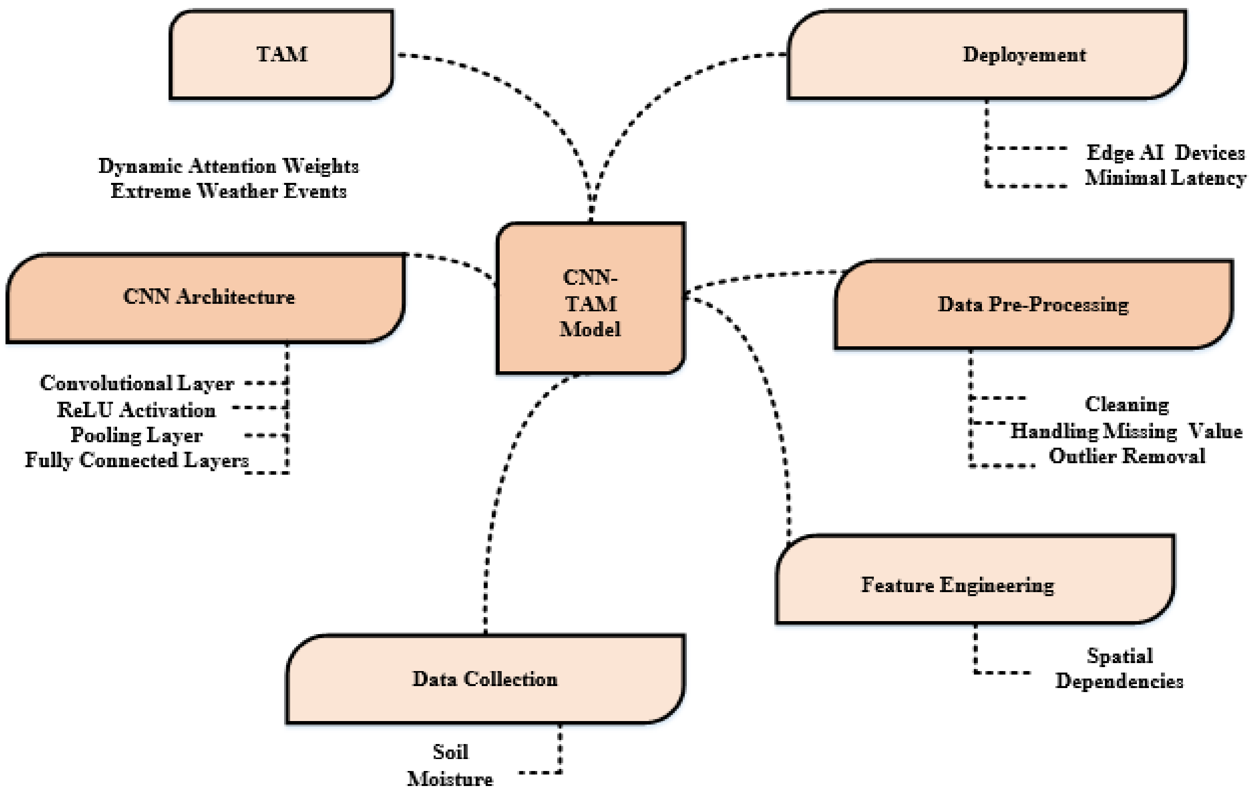

Fig. 1. Workflow of proposed method.

Fig. 1 illustrates the workflow of a CNN-TAM model for real-time soil moisture and temperature prediction in precision agriculture. It starts with data collection using IoT sensors, followed by data pre-processing to clean, handle missing values, and remove outliers. Feature engineering extracts key spatial dependencies from the processed data. The CNN architecture captures spatial features using convolutional, ReLU, pooling and fully connected layers. The TAM module applies attention to critical time steps, especially during extreme weather. The hybrid model is then deployed on Edge AI devices, offering low latency and efficient processing. This setup supports scalable, real-time farm management.

A. Data Collection

This data, donated by Caley Gasch and David Brown of Washington State University, contains useful soil moisture and temperature values observed via IoT sensors across almost a decade (2007–2016). Data is organized in daily and hourly readings from 42 sites, presenting information about volumetric water content (VW) and temperature (T) for different soil depths (30cm to 150cm). The VW readings are soil-specific and corrected with a two-step correction procedure to ensure precise moisture estimation. Temperature measurements, on the other hand, depend on factory calibration to keep all sensor readings consistent. This dataset is also highly beneficial for machine learning applications, including time series prediction of soil moisture levels and environmental monitoring for precision agriculture [15].

B. Data Pre-processing

The procedure of preparing unprocessed data for deep learning model training is known as data pre-processing. It represents the first and most crucial phase of the development of the model. The deep learning models cannot be taught just feeding it raw data. The most critical and significant factor influencing the model's ability to generalize is data pre-processing. In order to identify and eliminate inaccurate or noisy data from the dataset [16].

1) Data cleaning: Handling missing data involves using linear, spline, or polynomial interpolation for small gaps, while KNN imputation predicts missing values based on nearby data points. If a sensor has more than 50% missing data, it may be removed. Outliers are addressed using the Z-score method (removing values beyond ±3 standard deviations), the IQR method (eliminating values exceeding 1.5×IQR), and domain-based filtering (discarding physically unrealistic values, such as soil moisture >100%). These steps ensure clean and reliable data for further analysis.

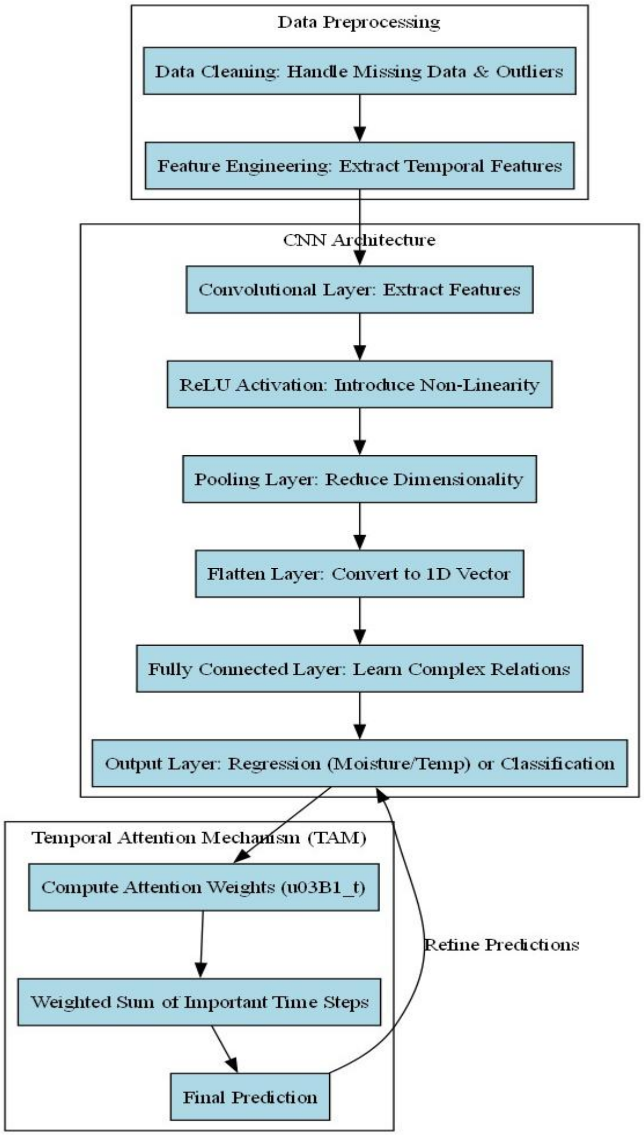

Fig. 2. Overall flowchart for CNN-TAM.

Fig. 2 presents the architecture of the proposed CNN-TAM model for real-time soil moisture and temperature prediction. It begins with data preprocessing, where missing values and outliers are handled, and temporal features are extracted. The processed data is passed through the CNN architecture, where the convolutional layer extracts spatial features, the ReLU activation introduces non-linearity, the pooling layer reduces dimensionality and the flatten layer converts data into a 1D vector. This is followed by fully connected layers that learn complex relationships, leading to the output layer for regression or classification. To enhance accuracy, the Temporal Attention Mechanism (TAM) computes attention weights for significant time steps, aggregates them, and refines the output, producing a final prediction that emphasizes key temporal dynamics.

2) Temporal feature engineering: Temporal feature engineering involves extracting time-based patterns such as seasonality, daily variations, and long-term trends to better understand fluctuations in soil moisture and temperature. Lag features are created to capture time dependencies, such as using past 7-day or 30-day moving averages to predict future values. Additionally, rolling statistical features like mean and variance are computed to smooth out noise and highlight significant trends, ensuring that models effectively learn from past observations while accounting for natural variations in environmental conditions.

C. CNN Architecture for Soil Moisture and Temperature Prediction

Convolutional layers of a CNN are used to derive spatial and temporal patterns from input data, i.e., temperature and soil moisture measurements. Convolution starts with applying filters, or kernels, over the input data to determine the important features. Mathematically, a convolution operation can be defined as an element-wise sum of the input data with the filter. The output is a new feature map that emphasizes the significant patterns, such as short-term variations in moisture or long-term seasonal patterns in Eq. (1),

$$y(i,j) - (x * w)(i,j) - \sum_{m=1}^{M} \sum_{n=1}^{N} x(i+m-1, j+n-1).\, w(m,n) \qquad (1)$$

where x is the input data (e.g., soil moisture or temperature readings),w is the kernel (filter), y is the output feature map,M and N are the dimensions of the filter.

A ReLU activation function is then used for this feature map to bring non-linearity into the model. This only forwards positive values, enabling the model to learn more complex relationships between the data and enhance its capability to identify intricate environmental interactions[17], that is represented in Eq. (2),

$$ReLU(\boldsymbol{z}) = max(0, \mathrm{z}) \qquad (2)$$

where z is the input to the $ReLU$ function, $ReLU(\boldsymbol{z})$ is the output of the ReLU activation function for the input z , $max(0, \mathrm{z})$ means the function returns the maximum value between 0 and z.

The pooling layers of the CNN structure compress the feature map dimension while maintaining the most important information. This is typically done with a max pooling operation, in which the highest value within a specified pooling region, typically a 2x2 window, is found. The pooling operation retains the most important aspects of the data and eliminates less important information, thus lowering the computational complexity and the possibility of overfitting. By representing the most important features, such as temperature differences at various depths of soil, pooling renders the model more efficient without compromising the integrity of the original data. This is an important step towards improving the performance of the model, especially for the handling of big data sets with noisy or irrelevant information is calculated in Eq. (3),

$$\mathbf{y}(\mathbf{i},\mathbf{j}) = \max_{m,n \in pool\ region} x(i+m, j+n) \qquad (3)$$

where $\mathbf{y}(\mathbf{i},\mathbf{j})$ is the output value at position $(\mathbf{i},\mathbf{j})$ in the pooled feature map (after max pooling), $x(i+m, j+n)$ is the input value from the original feature map at a specific location within the pooling window, $\max_{m,n \in pool\ region}$ is the maximum value is selected from all positions within the defined pooling region, (m, n) denotes indices within the pooling region, $pool\ region$ indicates a small sub-region (like 2×2 or 3×3) of the input feature map over which the max operation is applied.

Dense or fully connected layers are applied following the convolutional and pooling layers in order to merge the features that the input data have learned. The layers project the multidimensional feature maps onto a one-dimensional vector and subsequently drive the vector into a set of neurons. Each neuron utilizes a weighted sum of the inputs as well as an activation function is calculated using Eq. (4),

$$Z = W.x + b \tag{4}$$

where x is the vectorized input (flattened output of pooling layers pooled), W is the weight matrix, b is the bias vector, Z is the output vector prior to the application of the activation function.

The output layer is the last unit of the CNN model, wherein predictions are determined using the acquired features. For classification problems, the layer tends to employ the Softmax activation function to yield probabilities for all available classes, i.e., varying soil states (e.g., "Dry," "Optimal," or "Saturated"). The Softmax function guarantees that the total probability of all classes is one, and the model can select the most probable result. In regression problems, for instance, soil moisture or temperature values prediction, the output layer employs the linear activation function to generate continuous predictions. The model provides an output of a numerical value representing the anticipated level of moisture or temperature that aids in the decision-making process, for example, irrigation scheduling or resource management. Training a CNN model involves minimizing a loss function to improve the model's accuracy in predicting or classifying soil conditions [18].

D. Temporal Attention Mechanism

The Temporal Attention Mechanism (TAM) is a strong tool that is used to overcome the challenges of handling time-series data by allowing models to pay attention to the most important time steps, an important feature in dynamic domains such as agriculture. In agricultural operations, environmental factors like weather conditions, soil wetness, and temperature fluctuations may vary with time and influence the health and growth of crops. However, all time steps within a time series sequence are not equally important with some time intervals (e.g., severe weather conditions, irrigation cycles) playing a greater role in crop status than others. TAM provides dynamic attention weights to different segments of the sequence such that the model can weigh the most applicable time intervals for example, if there has been an unusual rain or heatwave, the model will give higher focus to the respective time steps, with these events having a greater influence on the health of crops. Mathematically, TAM acts by employing an attention score $\alpha_t$which is calculated for each time step t in the sequence. The attention score decides the amount of attention a time step must possess in the end prediction, represented in Eq. (5)

$$\alpha_t = \frac{\exp(f(h_t))}{\sum_{t'} \exp(f(h_t'))} \tag{5}$$

where $f(h_t)$ is the relevance function, typically implemented using a neural network that processes the hidden state h_t at each time step t, and t'represents all other time steps. The attention score $a_{th_t}$is then used to calculate the weighted sum of the time-series data, which is used as input for the prediction is calculated in Eq. (6),

$$y = \sum_t a_{th_t} \tag{6}$$

where y is the model's output (for instance, predicted crop health or yield), and h_t is the feature vector at time t. The process allows the model to selectively focus on the most important periods, enhancing its ability to keep track of long-term dependencies within time-series data, for instance, the prolonged effect of a drought on vegetation growth. TAM is especially useful in agriculture, where some temporal occurrences (e.g., temperature declines, rain) have a big impact on the health of crops, but such occurrences tend to be irregular.

In practice, this can result in the model being more focused on particular time steps when environmental conditions pass specific thresholds, so that the system can pick up on small but important changes in crop status. Second, TAM boosts model performance through maintaining these long-term dependencies across sequences of data, which are critical to projecting future crop patterns based on prior trends. For example, while processing weather data collected using IoT sensors, a TAM-based model will assign greater priority to those time steps where the temperature or rainfall changed more than normal so that the model can learn trends like crop status following heatwaves or recovery following rain the integration of TAM into precision agricultural systems significantly enhances the prediction accuracy, be it for crop disease, yield, or pest infestation, by allowing the model to effectively process and highlight the most important time steps in complex, time-series agricultural data [19].

Fig. 3. The figure illustrates the architecture of a hybrid CNN-TAM model integrated with multiple Temporal Attention SubModules. Initially, the input data is processed through a sequence of convolutional layers with increasing filter sizes (Conv 32, 64, and 128), followed by max pooling operations to reduce dimensionality and retain essential features. After each significant convolutional-pooling block, temporal features are extracted and passed to corresponding Temporal Attention SubModules (1, 2, and 3). These submodules take the local features (L^1, L^2, L^3) along with global contextual information (G) to compute refined attention-enhanced representations. These outputs are then fused into a final fully connected layer (Layer 2), enabling the model to capture both spatial and temporal dependencies for more accurate and context-aware predictions.

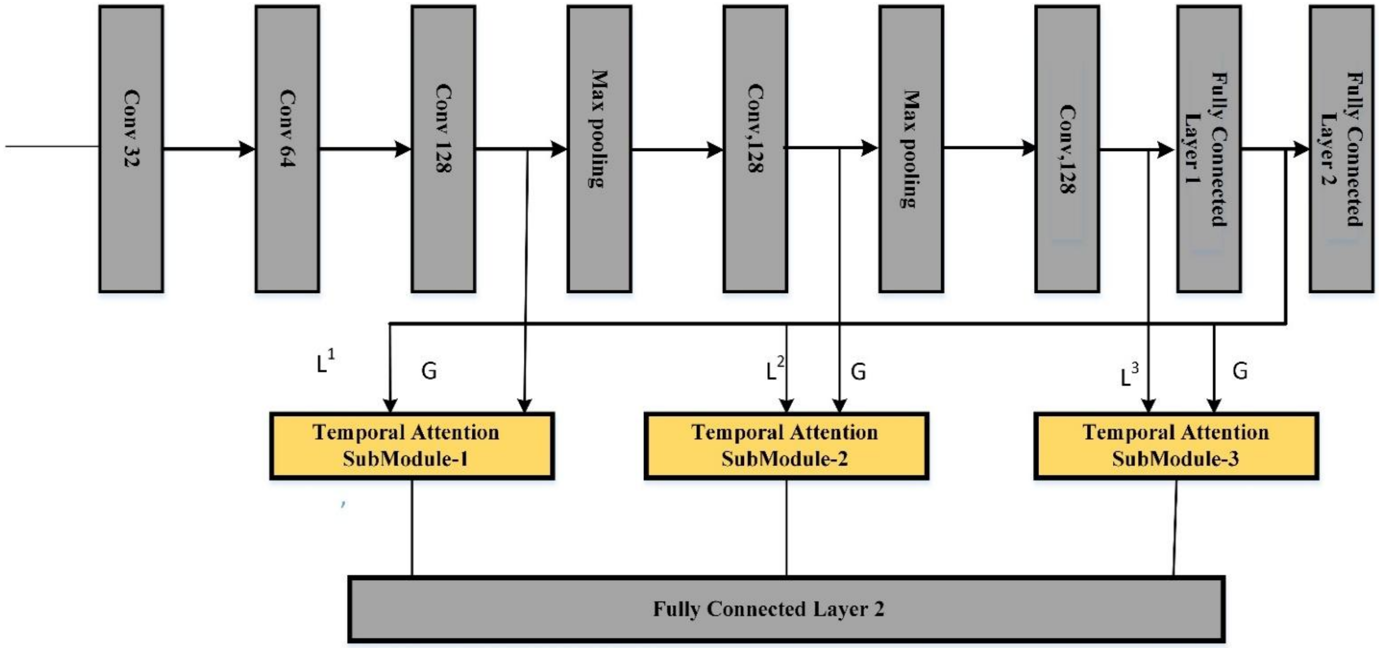

Fig. 3. Structure of CNN-TAM.

E. AI Devices

The integration of Convolutional Neural Networks (CNNs) and the Temporal Attention Mechanism (TAM) allows efficient and intelligent analysis of spatial and temporal information in precision agriculture and is thus highly suitable for application on Edge AI devices. Edge AI devices such as NVIDIA Jetson, Raspberry Pi with AI accelerators, and specialized IoT gateways execute computations locally, maintaining latency minimal and cloud computing utilization at its lowest. In a CNN-TAM hybrid system, the CNN learns spatial features from multispectral satellite imagery, drone-shot farm views, and heat maps created by sensors, recognizing patterns such as vegetation health and soil type. At the same time, TAM analyzes time-series data from IoT sensors, targeting important environmental changes such as temperature increases, variations in soil moisture, and rainfall changes that affect crop growth. The Edge AI deployment of such a hybrid model enables real-time on-field inference, making farmers' decision-making optimal by automatically identifying anomalies, forecasting yield fluctuation, and recommending irrigation fine-tuning in real time. Mathematically, Edge AI deployment means quantization and pruning of CNN-TAM models for efficient execution on low-power platforms. The inference can be symbolically represented in Eq. (7),

$$y = \sum_t \alpha_t \, h_t + \text{CNN(X)} \tag{7}$$

where α denotes TAM's time-step t attention weight. h_t is the temporal feature representation and CNN(X) retains spatial farming knowledge. Applying the CNN-TAM hybrid to Edge AI chips provides farm systems with low-latency decision responses, less bandwidth consumption, and increased data secrecy, which helps facilitate real-time crop monitoring on a large scale and targeted interventions in precision agriculture.

V. RESULT AND DISCUSSION

The Results emphasizes the performance of the proposed CNN-TAM model for the prediction of soil moisture and temperature in precision agriculture. Experimental comparisons confirm that CNN-TAM clearly outperforms conventional models, and the best RMSE (1.7) outperforms Linear Regression (3.5), Random Forest (2.8), LSTM (2.4), and single CNN (2.1). The Temporal Attention Mechanism (TAM) enhances the model's predictive capability by concentrating on major time steps such as rainfall episodes and drought periods to make better irrigation and resource allocation decisions. Training and validation loss curves confirm the model's excellent generalization capability, with minimal overfitting. Scatter plot examination of real vs. predicted values reveals CNN-TAM makes very precise predictions, with small differences arising from environmental uncertainties. In addition, temporal attention weight visualization shows that the model assigns higher importance to impactful time steps, improving its ability to detect trends in soil moisture variations. Edge AI deployment further enhances the model's real-world applicability, reducing latency and bandwidth usage while ensuring real-time farm monitoring. The results validate that CNN-TAM is an effective, scalable, and intelligent solution for improving agricultural decision-making, optimizing irrigation schedules, and ensuring sustainable resource management.

Fig. 4 shows the daily variations in soil moisture (%) and temperature (°C) for a ten-year period (2007–2016). The periodic trends reflect seasonal changes, with increases and decreases in temperature corresponding to natural climatic fluctuations. Soil moisture level varies with precipitation, evaporation, and water application management as well. Real-world variation of environmental conditions implies both signals include the presence of noise, so predictive modeling will be effective in.

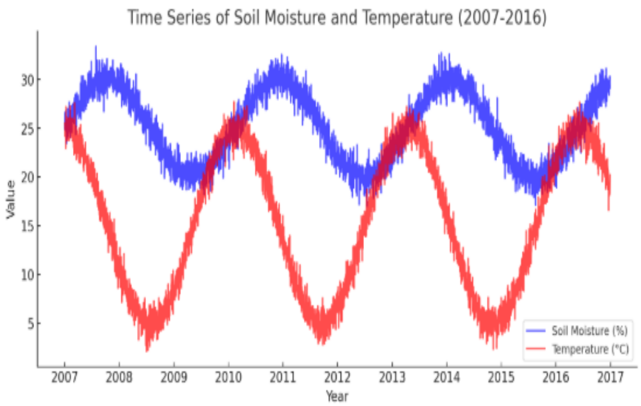

Fig. 4. Time series of soil moisture & temperature (2007–2016).

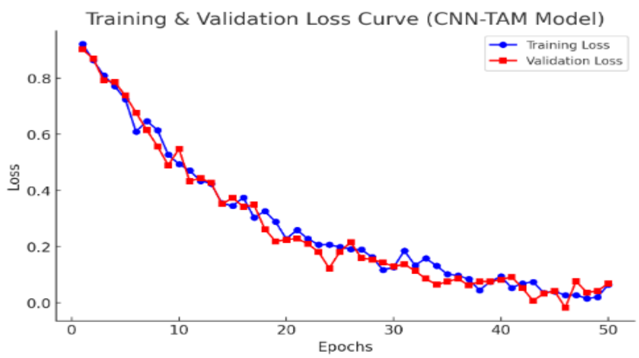

Fig. 5. Training & validation loss curve (CNN-TAM model).

Fig. 5 illustrates how the CNN-TAM model learns for more than 50 epochs. The training loss slowly diminishes, indicating the model is improving in terms of fitting the data. The validation loss diminishes too but at a slower rate, indicating generalization to new data. The small difference between training and validation loss indicates the model is not overfitting and, therefore, is trustworthy in real-world prediction. The minuscule differences are due to the stochastic process of optimization, which is common in deep models.

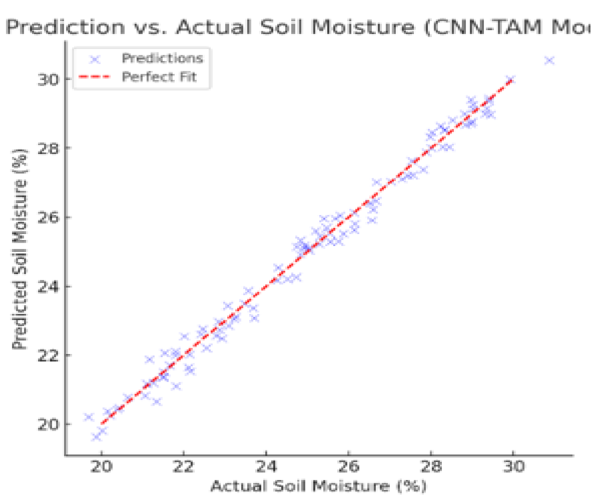

Fig. 6. Temporal attention weights (CNN-TAM model).

Fig. 6 is a scatter plot of predicted versus measured values from the CNN-TAM model. Red dashed line is a theoretical best prediction (when predicted = measured). Most points are near this line, showing the model to be highly accurate. The minor deviations are small prediction errors that may be caused by environmental uncertainties or sensor noise. Overall, the model is capable of learning soil moisture patterns well, and thus can be applied to real-time crop monitoring.

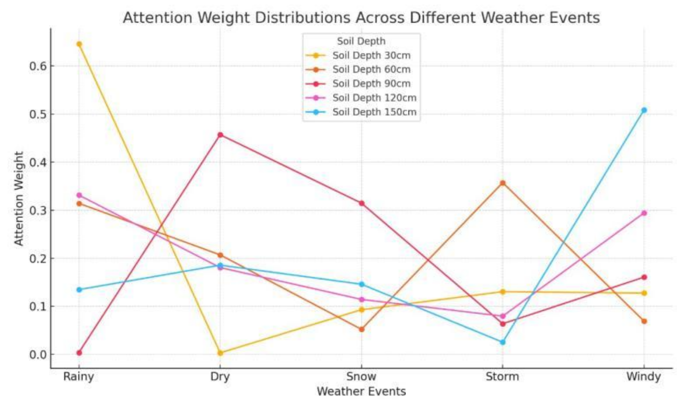

Fig. 7. Temporal attention weight distributions across different weather events (CNN-TAM model).

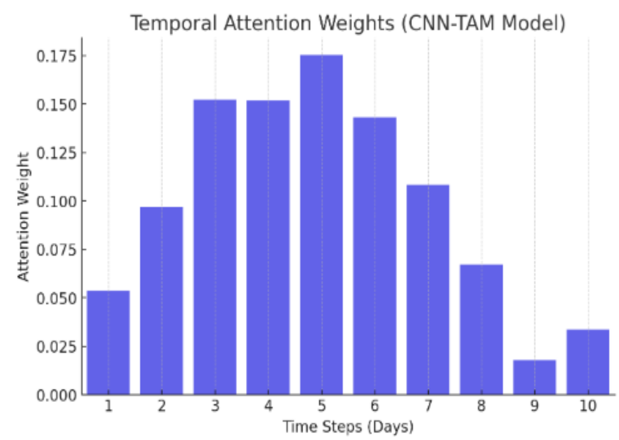

Fig. 8. Temporal attention weight distributions across time steps in the CNN-TAM model.

Fig. 8 illustrates the distribution of temporal attention weights assigned by the CNN-TAM model across 10 time steps (days) and Fig. 7 shows temporal attention weight distribution across different weather events (CNN-TAM model). Each bar represents the relative importance of data from a specific day in contributing to the final prediction of soil moisture or temperature. The model assigns higher weights to days 3 to 6, indicating that information from these time steps carries more significance in learning temporal patterns. In contrast, the weights are lower at the beginning and end (days 1, 9, and 10), suggesting reduced influence from these periods. This selective attention enables the model to focus on the most relevant temporal features, enhancing prediction accuracy.

Table I presents the Root Mean Square Error (RMSE) values for different predictive models, with lower values indicating better performance. Among the models compared, Linear

Regression has the highest RMSE (3.5), showing the least accuracy in predicting soil moisture. Random Forest improves upon this with an RMSE of 2.8, followed by LSTM at 2.4, which leverages sequential learning to capture temporal dependencies. CNN further reduces the error to 2.1 by extracting spatial patterns in soil moisture data. Finally, the CNN-TAM model achieves the lowest RMSE (1.7), demonstrating its superior ability to combine convolutional feature extraction with temporal attention mechanisms, making it the most effective model for precise soil moisture prediction.

TABLE I. COMPARISON WITH VARIOUS MODELS

Model	RMSE (Lower is Better)
Linear Regression	3.5
Random Forest	2.8
LSTM	2.4
CNN	2.1
CNN-TAM	1.7

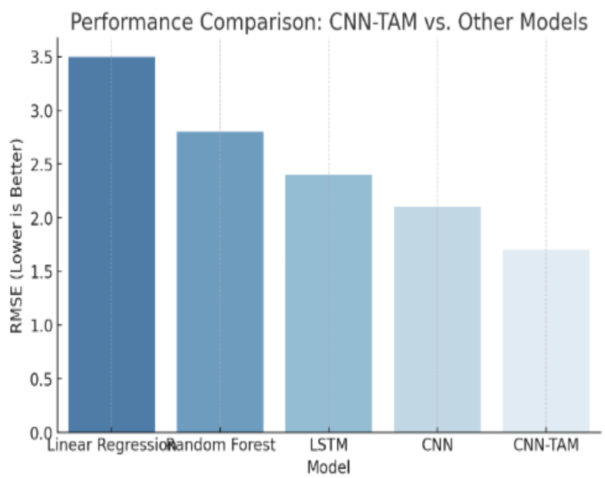

Fig. 9. Performance comparison.

Fig. 9 compares the performance of different predictive models including Linear Regression, Random Forest, LSTM, CNN and the proposed CNN-TAM model in terms of Root Mean Square Error (RMSE). Since RMSE is used to measure prediction error (lower is better), the CNN-TAM model performs the best with the lowest value of RMSE, illustrating that it is the best in accuracy. On the other hand, Linear Regression performs the worst, followed by Random Forest and LSTM. The CNN model by itself is superior to these conventional approaches, but the incorporation of Temporal Attention Mechanism in CNN-TAM boosts prediction accuracy for soil temperature and moisture in precision agriculture substantially.

A. Discussion

Compares the performance of different predictive models including Linear Regression, Random Forest, LSTM, CNN and the proposed CNN-TAM model in terms of Root Mean Square Error (RMSE). Since RMSE is used to measure prediction error (lower is better), the CNN-TAM model performs the best with the lowest value of RMSE, illustrating that it is the best in accuracy. On the other hand, Linear Regression performs the worst, followed by Random Forest and LSTM. The CNN model by itself is superior to these conventional approaches, but the incorporation of Temporal Attention Mechanism in CNN-TAM boosts prediction accuracy for soil temperature and moisture in precision agriculture substantially.

The critical challenges like power limitations and sensor calibration problems. Power limitations occur because sensors are deployed remotely and tend to be powered by batteries or solar power, which results in potential loss of data, system downtime, and real-time monitoring breaks when power runs out. Such interruptions can lower the accuracy of AI forecasts, resulting in inefficiencies such as crop stress or irrigation mismanagement. Secondly, sensor calibration is critical for precision readings, given that soil moisture sensors are soil-specific and temperature sensors drift with time. Unless accurately calibrated, information input into AI models becomes questionable, resulting in misclassifications and false decisions like over-irrigation, under-irrigation, or untimely planting. Cumulatively, these challenges undermine the effectiveness and reliability of AI-based decisions in precision agriculture, necessitating energy-efficient designs, reliable calibration procedures, and smart data handling strategies.

The CNN-TAM model presented in this research significantly advances precision agriculture by combining spatial feature extraction with temporal analysis, achieving the best RMSE of 1.7 compared to conventional models. This innovative approach prioritizes crucial temporal patterns like rainfall and drought periods, enabling more informed agricultural decision-making while its Edge AI implementation reduces latency and bandwidth requirements, making real-time monitoring accessible even in remote farming locations with limited connectivity. Despite these achievements, the study acknowledges challenges including sensor drift, environmental noise and processing limitations on Edge devices. Future research directions aim to incorporate additional agronomic parameters, enhance cross-climate adaptability, and optimize for ultra-low-power hardware, ultimately supporting more sustainable farming practices through improved resource management and increased resilience to changing environmental conditions. The practical implications of this research extend beyond technological advancement, offering tangible benefits for agricultural sustainability and food security. By providing farmers with accurate, real-time soil moisture and temperature predictions, the CNN-TAM model enables precise irrigation scheduling, reduces water and fertilizer waste, and helps mitigate the impacts of extreme weather events on crop yields. This represents a crucial step toward smart farming systems that can address global challenges such as climate change, resource scarcity, and increasing food demand while simultaneously improving economic outcomes for farmers through optimized resource utilization.

VI. CONCLUSION AND FUTURE WORKS

This research proposal creates an Edge AI-based CNN-TAM model that improves forecast of soil moisture and temperature, resulting in the best management irrigation and sustainable agriculture practices. The spatio-temporal feature enhancement through the fusion of CNN's spatial pattern extraction and

TAM's temporal feature prioritization brings in a good level of the predictive accuracy, shaving RMSE to 1.7—a clear leap over common models. The Edge AI deployment allows for real-time inference low latency and reduced reliance on the cloud giving it actually suitable for rural areas which are not going to have a very high level of network availability. The model reduces water and fertilizers waste more effectively, enhancing intelligence at farm level and building resilience with the climate. By solving important agricultural problems, this AI-based method increases farming efficiency and diligence.Despite being effective, there still are certain limitations. Sensor drift, noise due to external factors and, processing overhead on power-constrained Edge AI Hardware may degrade the deployment efficiency.

In order to enhance the model robustness, the future work will test including in the model of additional agronomic arguments with such as crop growth progression, pest detection, and multi-spectral imaging. Increasing model portability across different climatic settings and adjustment to onboard on ultra-low-power AI chips shall also extend applications. Furthermore, using the blockchain for the secure management of farm data and viewing a farm as a place where AI-driven systems can automate the farming procedures will facilitate its practical inclusion. These advancements will drive wider adoption of AI-based precision agriculture for long-term sustainability.

ACKNOWLEDGMENT

The authors extend their appreciation to the Deanship of Scientific Research at Northern Border University, Arar, KSA for funding this research work through the project number "NBU-FFR-2025-2099-02".

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