JellyNovaNet-JSO: A Hybrid TabNet–BiLSTM Model for IoT-Based Crop Yield Prediction

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***Abstract*—Precise prediction of crop yield is essential for sustainable agriculture, resource maximization, and food security. As the use of IoT and Wireless Sensor Networks (WSNs) gains momentum, huge amounts of heterogeneous and time-series environmental data have become readily available from intelligent greenhouses. Despite this, it is still difficult to obtain meaningful insights from these data due to their high dimensionality, noise, and nonlinear temporal behavior. Traditional machine learning and statistical approaches usually fail to effectively capture static as well as sequential relationships, and most current models are difficult to tune hyperparameters and have problems with dealing with data heterogeneity and do not generalize across dynamic environments. To overcome these shortcomings, this paper introduces JellyNovaNet-JSO, a new hybrid deep learning architecture that integrates TabNet and BiLSTM architectures, designed using the Jellyfish Search Optimization (JSO) algorithm. The model exploits TabNet sparse attention for static feature modeling and the temporal memory of BiLSTM for time-series sensor data. The innovation is in utilizing attention-guided tabular learning with bidirectional temporal modeling, with a metaheuristic optimization layer to perform automatic hyperparameter tuning. Experimental outcomes based on real-world IoT greenhouse data demonstrate that JellyNovaNet-JSO attains MAE of 0.012, RMSE of 0.017, R^2 of 0.991, and MAPE of 1.89%, outperforming state-of-the-art CNN-LSTM, Random Forest, and SVM models substantially. In comparison with the prior approaches, JellyNovaNet-JSO enhances prediction accuracy by as much as 25% while ensuring scalability and robustness. This innovation provides a viable, interpretable, and deployable solution for precision agriculture, enabling smarter irrigation, climate control, and yield management.**

***Keywords*—IoT agriculture; crop yield prediction; BiLSTM; TabNet; jellyfish search optimization**

I. INTRODUCTION

Accurate crop yield estimation is a key consideration in modern agriculture, as a valuable decision-making aid for farmers, policymakers, and stakeholders to rely on food production [1], resource deployment, and planning for marketing [2]. With the world's population increasing and agricultural land shrinking, crop yield maximization is needed to ensure food security and sustainable agricultural output [3]. Sufficient and reliable yield estimates enable risk avoidance of adverse weather conditions, infestation by pests, and other environmental factors that could seriously hinder agricultural output [4]. Furthermore, authentic predictions enable proper input management at minimal cost in the form of water, fertilizers, and pesticides, thereby reducing costs as well as environmental deterioration [5]. Advances in technology, especially the integration of Internet of Things (IoT) devices and Wireless Sensor Networks (WSNs), have revolutionized the ability to monitor real-time environmental parameters across large agricultural fields [6]. Such a proliferation of data availability, though, comes with the difficulty of extracting useful information from high-dimensional, time-series, and intricate data [3]. Hence, it becomes imperative to develop robust predictive models that can accommodate heterogeneous types of data and temporal patterns [5]. These models not only facilitate proactive crop management but also propel sustainable agrarian practice by optimizing the utilization of resources and minimizing wastage [7]. Therefore, enhancing the accuracy and reliability of crop yield prediction models remains a top agenda for agriculture research, driving developments in machine learning [8], deep learning, and optimization techniques tailored to the unique demands of smart agriculture [6].

While great potential of IoT and Wireless Sensor Networks resides in agriculture, accurate estimation of crop yields is stifled by numerous significant challenges [1]. One of the significant challenges is the complexity and heterogeneity of the environmental data perceived by the different sensors monitoring variables such as temperature, humidity, soil nutrient concentrations, and water levels [9]. They are likely to exhibit nonlinear relationships and interact with each other in intricate ways that are difficult to model with traditional statistical techniques [10]. Furthermore, the data tend to be high-dimensional and noisy and contain missing entries and measurement errors due to sensor imperfections or environmental perturbations [11]. Another principal challenge is to model temporal dependencies and dynamic patterns inherent in agriculture processes [1]. Crop development and yields are contingent upon time-series fluctuations in environmental variables, so models need to be capable of learning long and short-term dependencies in sequential data [12]. Seasonal variations, soil nutrient lag effects, and periodic irrigation cycles make the time-scale modeling task even more complicated. In addition, the integration of static tabular information (e.g., crop type, soil type) with sequential sensor data contributes to the difficulties encountered by predictive modeling [9]. These challenges call for advanced machine learning paradigms with the capacity to deal with heterogeneous time-dependent information that also demands interpretability and robustness [10]. Overcoming these challenges is central in the development of plausible crop yield prediction systems deployable in real-world smart farming contexts [13].

The emergence of the IoT and WSNs [9] has revolutionized the field of agriculture through continuous, real-time

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monitoring of environmental parameters with unparalleled detail [14]. IoT is a network of physical objects with sensors, actuators, and communication modules which are connected with each other and communicate with the help of the internet or local networks [15]. In farming, IoT sensors track vital parameters including soil moisture, temperature, humidity, light levels, and nutrient content, and present farmers with accurate data to facilitate optimal crop care[16]. Additionally, WSN are spatially distributed nodes of sensors that wirelessly interface to a central gateway, allowing for flexible and extensible data collection in large-scale farms or contained environments such as greenhouses[17]. WSNs have the benefit of simple deployment, low power requirements, and environmental challenge resistance, thus being well suited for agricultural monitoring[18]. The combination of IoT and WSN technologies produces rich, multivariate, and time-stamped data that represents dynamic interactions between crop and environment[18], [19]. This richness in data provides the foundation for building advanced predictive models to enhance yield forecasting, resource management, and sustainable agriculture[20], [21], [36].

To address the issues concerned with crop yield prediction from heterogeneous and time-series farm data, this research presents JellyNovaNet-JSO, a new hybrid model that combines synergistically the merits of TabNet and Bidirectional Long Short-Term Memory (BiLSTM) networks, fine-tuned by the Jellyfish Search Algorithm (JSA). TabNet, being interpretable and having the capacity to effectively process tabular data, excels at capturing significant features from static or non-temporal environmental conditions such as water levels and soil moisture. On top of that, BiLSTM captures temporal dependencies and bidirectional contextual information from sequential sensor inputs such as temperature and humidity across time, which are crucial in modeling crop growth dynamics. The combination of these two architectures enables the model to utilize both static and sequential data modalities in an optimal manner and hence improves prediction accuracy. To further optimize model performance, the Jellyfish Search Algorithm as a bio-inspired metaheuristic search approach is employed in tuning major hyperparameters such as learning rates, layer dimensions, and batch setup. This optimization not only improves convergence but also avoids local minima, resulting in a robust and reliable crop yield prediction model ready for use in real-world smart agriculture scenarios.

This research makes the following key contributions:

1) Introduced a novel hybrid model, JellyNovaNet-JSO, which combines the TabNet architecture with BiLSTM networks. The model is optimized using the Jellyfish Search Algorithm (JSO) to improve the accuracy and efficiency of crop yield prediction in IoT-enabled greenhouse environments.

2) Leveraged real-time data collected from IoT-based sensors and wireless sensor networks deployed in a smart greenhouse to model crop growth patterns and predict yield.

3) Incorporated advanced data preprocessing techniques, including timestamp conversion, feature scaling, and temporal feature engineering. These methods enhance the model's ability to learn from both static and temporal features, improving prediction accuracy. The BiLSTM component of the proposed hybrid model captures bidirectional temporal dependencies in time-series sensor data. This is essential for modeling complex, long-term, and short-term crop growth patterns, which are influenced by changing environmental conditions.

4) Conducted a thorough estimation of the model using several performance metrics, including MSE and R^2, to assess the accuracy of crop yield predictions. The approach is validated through the prediction of crop yields in a real-world IoT-enabled greenhouse setup.

The rest of this paper is structured as follows:

- Section II summarizes recent publications on IoT and ML/DL-based crop yield prediction, citing current drawbacks.
- Section III formulates the problem statement and states the main goals encompassing scalability, heterogeneity of data, adaptability, and tuning.
- Section IV presents the envisioned JellyNovaNet-JSO hybrid model, including its architecture, elements (TabNet, BiLSTM), preprocessing pipeline, and JSO optimization.
- Section V offers results of experiments, such as evaluation measures, attention analysis, ablation analysis, and performance comparisons with other models.
- Section VI summarizes the study and proposes directions for future work such as real-time deployment and multi-location validation.

II. Related Works

N. Chandiraprakash et al. [14] created a crop yield forecasting model that combined real-time IoT sensor data with state-of-the-art ML algorithms, such as LSTM and Random Forest, to facilitate better adaptation to climatic variability. They also investigated the integration of CNN with LSTM to achieve higher spatial-temporal prediction accuracy. They had a user-friendly interface as part of actionable farmer insights for precision agriculture. Rath et al. [22] suggested a precision farming methodology based on the use of real-time wireless sensor network data for enhanced accuracy in crop yield forecasting. Their model incorporates sensor feeds on a continuous basis through a mobile app, providing timely prediction and real-time data gathering capabilities. The research discusses the advantages of utilizing sensor-assembled data from many users for improving model training. Haritha et al. [23] worked on a supervised machine learning method of crop prediction based on climatic and soil factors like humidity, temperature, and nutrient levels. They tested various classifiers like Naïve Bayes, AdaBoost, Decision Tree, and Voting Classifier and determined that the Decision Tree algorithm ranked highest with 99.4% accuracy. The work is centered on enhancing prediction accuracy to help farmers in selecting crops in fluctuating climatic conditions. Çetiner et al. [3] suggested a hybrid deep model of LSTM and CNN to automatically predict crop yields with major parameters like water consumption, exposure to sunlight, fertilizers, pesticides, and fields of cultivation. Their model provided good predictive power with an R^2 measure of 89.71 along with low error metrics, establishing competitiveness for state-of-the-art methods.

Prathap et al. [24] investigated an IoT-based intelligent agriculture system to enhance crop yield prediction and automated monitoring to minimize human involvement. Their method combines sensors and cameras to monitor yield levels, uploading real-time data to the cloud for analysis. A hybrid deep learning algorithm is used in the study to improve prediction accuracy in smart agriculture systems. Sensor reliability and integration of data issues still exist for fully automated systems. Gupta and Nahar et al. [25] created a hybrid machine learning system with IoT data for crop yield prediction, incorporating preprocessing, feature extraction, and classification steps. The two-level approach utilizes aKNCN for classifying soil quality and ELM with an improved BOA for predicting yields. The model revealed better accuracy and reduced errors on soil datasets with varied evaluation measures. Manikandababu et al. [26] examined how machine learning algorithms and IoT technologies can be integrated to improve crop production prediction in precision agriculture. They employed sensor and drone data measuring crop health, weather, and soil moisture for informing models. This method allows farmers to make informed decisions regarding pest control, fertilization, and irrigation, increasing yield accuracy. N. Mohana Priya et al. [27] conducted a study on the combination of ML and IoT for the optimization of irrigation management based on real-time sensor readings of temperature, humidity, soil moisture, and water level. They compared models with SVM resulting in the highest accuracy of pump operation prediction. The study showcases the capability of IoT and ML to make adaptive, data-driven control of irrigation for better water use efficiency. Pérez et al. [28] created a tomato crop forecasting system combining AI, sensor networks and IoT to balance resource utilization and improve forecasting yield. The framework included distributed sensors, IoT gateways, and cloud-based recurrent neural network models that were trained on environmental information and tested with harvest data. Their model had an average prediction error of 3.2% over a period of four weeks, reflecting high accuracy.

Kumar et al. [29] implemented an ensemble ML model for crop prediction from IoT sensor data gathered using the PLX-DAQ tool, integrating algorithms. Their ensemble method has a very high accuracy of 97.45% for early crop yield prediction. Their work showcases the strength of an IoT and ML integration for maximizing data-driven decisions in agriculture amid the threats posed by climate change. Yet, the dependency on sensor integration and data quality continues to be a bottleneck in sweeping adoption. Krithika et al. [30] explored DL model applied for crop yield prediction based on real-time agricultural datasets. The experiments showed that although all models were promising, LSTM was most accurate because it can learn temporal dependencies in the data. The research underscores the importance of improving ML models further to improve attempts in mitigating challenges brought by natural disasters. Rastog et al. [31] proposed an AI and ML approach with Python to improve crop yield prediction and assist farmers in the Indian subcontinent by leveraging IoT and Cyber-Physical systems. Their research is intended to tackle food security issues by making timely predictions of yield, moisture, and weather conditions. The research endeavors to enhance prediction accuracy through sophisticated learning algorithms on authentic agricultural datasets.

Although recent work shows substantial advancements in using IoT and machine learning for crop yield estimation and precision farming, some universal limitations are still prevalent. Computational complexity and scalability issues of hybrid CNN-LSTM models were noted by Chandiraprakash et al. [14] in large-scale implementations. Rath et al. [22] mentioned issues with handling heterogeneous sensor data and maintaining model scalability across various agricultural environments. Haritha et al. [23] pointed out that models based on fixed datasets could face challenges in coping with dynamic climatic conditions. ÇetiNer et al. [3] highlighted the reliance on precise parameter measurement and rigorous fine-tuning for consistent model performance. Prathap et al. [24] indicated challenges with sensor reliability and data integration as challenges to complete automation. Gupta and Nahar et al. [25]found that the use of hyperparameter tuning would restrict generalizability in various contexts of farming. Manikandababu et al. [26] had mentioned difficulties in large-scale deployment and integration of data. Mohana Priya et al. [27] reported misclassification error in irrigation control predictions in need of further tuning. Pérez et al. [28] showed high accuracy but recognized the necessity for strong system integration. Kumar et al. [29] and Rastog et al. [31]pointed to bottlenecks in sensor quality data and scalability challenges for mass implementation. Taken together, the studies point toward the fact that in addition to much encouraging work, challenges like heterogeneity of data, computational costs, reliability of sensors, robustness of models, and scalability need to be overcome to achieve the complete potential of IoT and ML in smart agriculture.

III. Problem Statement

In spite of remarkable progress in unifying IoT and machine learning for crop yield prediction, some urgent limitations obviate widespread use and performance. First, most models are computationally expensive and lack scalability when applied in practical large-scale agricultural settings [14]. Second, data heterogeneity and sensor unreliability issues impair input data quality and uniformity, degrading model robustness [22]. Third, the reliance on fixed or static datasets lowers the models' responsiveness to dynamic and rapidly evolving environmental conditions [23]. Lastly, most current models are sensitive to hyperparameters that need to be heavily tuned and fine-tuned, affecting generalizability across a wide range of farming contexts [25]. Such constraints warrant more effective, adaptive, and scalable precision agriculture solutions.

Research Objectives

- Develop a computationally efficient hybrid model that maintains high accuracy while enabling scalability for large-scale agricultural deployments.
- Design robust data preprocessing and sensor fusion techniques to handle data heterogeneity and improve sensor data reliability.

- Incorporate dynamic learning mechanisms that adapt to changing environmental and climatic conditions in real-time.

- Implement an automated hyperparameter optimization framework to enhance model generalizability and reduce manual tuning efforts.

IV. Proposed Methodology for Crop Yield Prediction Using IoT and Wireless Sensor Networks

The methodology for crop yield prediction put forward uses a hybrid machine learning model, JellyNovaNet-JSO, that combines the TabNet and BiLSTM architectures, optimized using the JSO. The proposed methodology takes advantage of the robustness of both the TabNet model, specifically developed for effective processing of tabular and categorical data, and the BiLSTM model, which is able to recognize bidirectional temporal patterns in time-series data. The model initially handles static attributes such as soil nutrient content and actuator states through TabNet, whereas BiLSTM extracts the dynamic behavior of sequential sensor readings from IoT-connected greenhouses. These models are then combined to merge spatial and temporal information so that accurate and efficient crop yield prediction can be supported. With timestamped features, feature scaling, and time series windowing, the hybrid method offers comprehensive modeling of environmental circumstances and their impacts on crop growth while providing a more robust setting for yield prediction in smart agricultural applications. Fig. 1 demonstrates the step-by-step methodology for crop yield prediction using the JellyNovaNet-JSO hybrid model integrating IoT sensor data and machine learning techniques.

A. Data Collection

The dataset in the present research was obtained as part of research for the master's thesis carried out by Mohammed Ismail Lifta (2023-2024) at Tikrit University, Iraq [32]. The data was obtained from a mounted smart greenhouse that is equipped with advanced IoT-enabled sensors and actuators. Environmental conditions such as, humidity, temperature, water level, and soil nutrient concentrations (nitrogen, phosphorus, potassium) were sensed in real time through wireless sensor nodes placed around the greenhouse. Actuator status such as fan and pump ON/OFF signals were also recorded in order to express environmental control decisions. Data, spanning multiple months and comprising 37,923 records, were remotely transmitted and stored via a cloud-capable application linked to Google Sheets for real-time monitoring and regulation of the greenhouse climate. The high-density, time-stamped, multivariate data are most suitable for modeling crop growth patterns and yield prediction using IoT and Wireless Sensor Network technologies. This Table I shows exemplary data of time-stamped sensor measurements read from the smart greenhouse. It further depicts actuator statuses reflecting the state of operation of the fan and watering pumps, capturing environmental conditions as well as control actions. The data corresponds to tomatoes grown in the smart greenhouse for four continuous months in 2023-2024. During preprocessing, minor issues were noted and handled: missing entries, sensor drift, and dropped packets. The complete dataset is available for reproducibility at:

https://www.kaggle.com/datasets/wisam1985/iot-agriculture-2024

B. Data Preprocessing for JellyNovaNet-JSO Model

Some preprocessing steps need to be carried out after having a clean dataset with one-hot encoded values captured from the smart greenhouse sensor network before being modeled efficiently using the JellyNovaNet-JSO hybrid architecture. The main tasks include timestamp conversion, feature scaling, temporal feature engineering, time series windowing, and separating the dataset into training and testing so that data leakage does not occur.

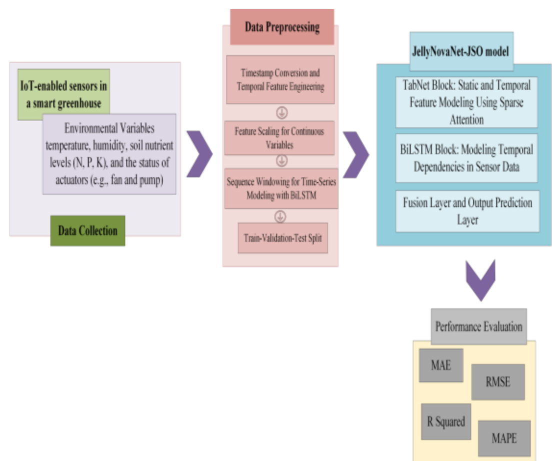

Fig. 1. Methodology flow for crop yield prediction using JellyNovaNet-JSO hybrid model.

TABLE I SAMPLE ENVIRONMENTAL AND ACTUATOR SENSOR DATA FROM SMART GREENHOUSE

Date & Time	Temperature (°C)	Humidity (%)	Water Level (%)	N (0-255)	P (0-255)	K (0-255)	Fan actuator ON	Watering plant pump ON	Water pump actuator ON
2024-02-08 06:10:00	41	63	100	255	255	255	1	1	1
2024-02-08 06:15:00	41	59	100	255	255	255	1	1	1
2024-02-08 06:20:00	41	62	100	255	255	255	1	1	1
2024-01-18 05:02:00	37	62	100	255	255	255	1	1	1
2024-01-18 05:07:00	37	63	100	255	255	255	1	1	1

1) Timestamp conversion and temporal feature engineering: The dataset contains a critical Date and Time column representing the exact timestamp for each sensor reading. To leverage temporal patterns and seasonality effects in crop growth, this column must be converted into a datetime data type compatible with modeling frameworks as given in Eq. (1)

$$\text{Timestamp}_{i} = \text{datetime}(\text{Date \& Time } i) \quad (1)$$

This conversion enables extraction of granular temporal features such as hour of day, day of month, month, and day of week, which can serve as additional predictors to improve model performance. These features are mathematically derived from the timestamp as given in Eq. (2).

$$\begin{aligned} \text{Hour}_{i} &= \text{Timestamp}_{i}.\text{hour} \\ \text{Day}_{i} &= \text{Timestamp}_{i}.\text{day} \\ \text{Month}_{i} &= \text{Timestamp}_{i}.\text{month} \\ \text{DayOfWeek}_{i} &= \text{Timestamp}_{i}.\text{weekday} \end{aligned} \quad (2)$$

Incorporating these gyclic temporal components allows the model to capture daily and seasonal variations inherent in environmental and crop growth data.

2) Feature scaling for continuous variables: The continuous sensor features, including temperature, humidity, water level, and soil nutrient concentrations (nitrogen, phosphorus, potassium), span different numerical ranges. To prevent features with larger scales from leading the learning process and to accelerate convergence during training, feature scaling is necessary. The Min-Max scaling technique normalizes these features to a fixed range [0,1], using Eq. (3).

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (3)$$

where x_i is the actual feature value, and $x_{\text{min}}, x_{\text{max}}$ are the min and max values of that feature across the dataset.

3) Sequence windowing for time-series modeling with BiLSTM: BiLSTM networks need sequential input data that capture temporal dependencies. To convert the continuous sensor data into appropriate time-series format, a sliding window approach was applied. With a defined window size ω, consecutive segments of the dataset were extracted as input sequences, as shown in Eq. (4).

$$S_t = [x_t, x_{t+1}, \dots, x_{t+w-1}] \quad (4)$$

where S_t is the sequence input at time step t and x_i is the feature vector at timestamp i.

The target label (e.g., crop yield or environmental condition at $+w$) can be associated with each sequence, enabling supervised learning. The choice of window size balances capturing long-term dependencies without making the sequence overly large, typically ranging from 5 to 30-time steps depending on data frequency.

4) Train-validation-test split: To simulate real-world forecasting and prevent data leakage, the dataset is split chronologically rather than randomly. The data are divided into three subsets, given in Eq. (5).

$$\begin{cases} \text{Training set} & : \quad \text{first } 70\% \\ \text{Validation set} & : \quad \text{next } 15\% \\ \text{Test set} & : \quad \text{final } 15\% \end{cases} \quad (5)$$

Such time-based splitting confirms that the model is tested on future unseen data, mimicking actual deployment scenarios in crop yield prediction.

The data preprocessing pipeline caters to the requirements of JellyNovaNet-JSO, that is, it transforms cleaned one-hot encoded raw data into an appropriate format. The steps involved are timestamp parsing, temporal feature generation, normalization of continuous variables, creation of sequential windows for BiLSTM input, and finally the time-aware train/test split. Thus, the hybrid model can indeed grasp the complexities involved in spatio-temporal patterns of an IoT-enabled greenhouse environment to finally provide correct crop yield estimations.

```
Pseudocode: Data Preprocessing for JellyNovaNet-JSO
Input: RawDataset.csv  # IoT-based greenhouse sensor data
Output: Preprocessed training, validation, and test sets

BEGIN

1. Load Dataset
   Dataset ← read_csv("RawDataset.csv")

2. Timestamp Conversion
   For each record in Dataset:
      Timestamp_i ← to_datetime (Dataset ["Date & Time"] [i])

3. Temporal Feature Engineering
   For each Timestamp_i:
      Hour_i      ← Timestamp_i. hour
      Day_i       ← Timestamp_i.day
      Month_i     ← Timestamp_i. month
      DayOfWeek_i ← Timestamp_i. weekday
   Append Hour, Day, Month, DayOfWeek as new columns to Dataset

4. Feature Scaling using Min-Max Normalization
```

```
    For each continuous feature f ∈ {Temperature, Humidity, WaterLevel, N, P, K}:
        f_scaled ← (f - min(f)) / (max(f) - min(f))
    Replace original features with scaled features

  5. Sequence Windowing for Time-Series Input
    Define window_size w
    Sequences ← []
    Labels ← []
    For i from 0 to (length (Dataset) - w):
        Sequence ← Dataset [i: i+w]
        Label ← Dataset [i + w] ["Crop_Yield"]
        Append Sequence to Sequences
        Append Label to Labels

  6. Chronological Train-Validation-Test Split
    total_samples ← length (Sequences)
    train_end ← 0.70 * total_samples
    val_end ← 0.85 * total_samples

    TrainSet ← Sequences
    Train Labels ← Labels

    ValSet ← Sequences
    ValLabels ← Labels

    TestSet ← Sequences
    TestLabels ← Labels

  7. Return TrainSet, ValSet, TestSet and corresponding labels

  END
```

C. *Model Development*

To apply the JellyNovaNet-JSO model a Jellyfish Search Optimized variant of TabNet and BiLSTM for precise crop yield forecasting. The suggested JellyNovaNet-JSO model is a hybrid DL system combining the features of TabNet and BiLSTM networks, JSO-optimized to improve the precision of crop yield forecasting in IoT-based greenhouse setups. The model starts with a TabNet layer, which is particularly suited to process the heterogeneous tabular and categorical features like nutrient contents (N, P, K), actuator states (fan/pump ON/OFF), and engineered temporal variables (hour, day, month). TabNet applies a sparse attention mechanism to softly select relevant features at every decision step in order to make the model interpretable and learn efficiently from high-dimensional structured data. In parallel to this, the BiLSTM module handles the sequential input from time-series sensor reading data (e.g., water level, temperature, humidity) formatted into sliding windows. The BiLSTM can model intricate bidirectional temporal relationships, allowing the model to learn past and future contextual patterns affecting crop development. The features from TabNet and BiLSTM are then input into a layer of feature fusion, where they are concatenated and optionally smoothed by dense layers to facilitate cross-modal interaction between static tabular knowledge and dynamic temporal patterns. Lastly, the fused representation is input into a fully connected output layer that predicts the final continuous crop yield. This hybrid architecture guarantees that the model is efficiently able to capture the spatial and temporal complexities of IoT greenhouse data, while JSO integration further boosts the performance of the model using smart hyperparameter tuning.

1) TabNet block: Static and Temporal Feature Modeling Using Sparse Attention.

The TabNet block is used to process the tabular and categorical features of IoT sensor data and temporal encodings. They consist of static variables such as soil nutrient content (N, P, K), actuator states (fan ON/OFF, water pump state), and engineered time-based features like hour, day, month, and day of the week - all of which are pivotal in comprehending crop growth dynamics in smart greenhouses. Fig. 2 shows the TabNet architectural diagram and their components are explained briefly given below.

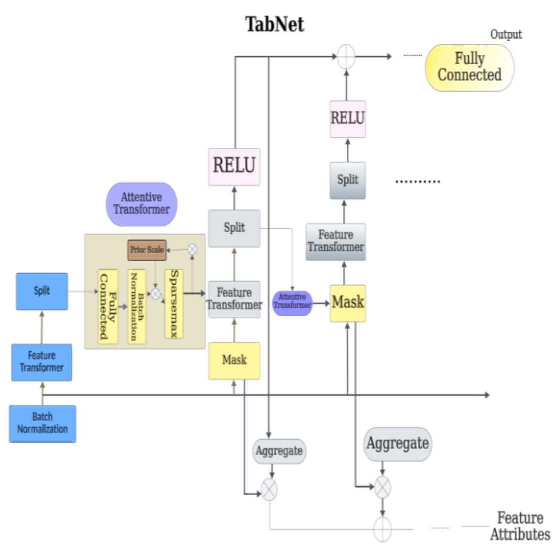

Fig. 2. TabNet architectural diagram.

Input Representation:

Let the input feature vector be represented as in Eq. (6).

$$X = \{x_1, x_2, \dots, x_n\} \in \mathbb{R}^n \quad (6)$$

where each $\boldsymbol{x_i}$ corresponds to a scaled and encoded feature (e.g., N, P, K, actuator state, hour, day, etc.), and $\boldsymbol{n}$ is the entire number of tabular features.

a) Feature transformer: Each input is passed through a feature transformer, which contains fully connected layers, batch normalization, and non-linear activation functions. This layer learns complex feature interactions and generates a richer representation of the input. For a layer $\boldsymbol{l}$, the transformation can be described as in Eq. (7).

$$H^{(l)} = ReLU\left(BN\left(W^{(l)}H^{(l-1)} + b^{(l)}\right)\right) \tag{7}$$

Where, $W^{(l)}$ *and* $b^{(l)}$ are weights and biases at layer l, $BN(\cdot)$ denotes batch normalization, $H^{(0)} = X$

The output $H^{(L)}$ of the final transformer layer is used as the latent feature embedding for downstream fusion.

b) Sparse attentive masking: To focus on the most relevant features at each decision step, TabNet incorporates a sparse attention mechanism. This mechanism generates feature masks M_i using the softmax and sparsemax functions. For a decision step i, the mask is computed as using Eq. (8).

$$M_i = sparsemax\left(P_{i-1} \cdot H^{(i)}\right) \tag{8}$$

Here, $H^{(i)}$ is the transformer output at step $\boldsymbol{i}$, $\boldsymbol{P_{i-1}}$ is the prior scale that limits the reuse of features (to promote sparsity), sparsemax (-) encourages hard selection of features, improving interpretability.

The masked input passed to the next decision step is given by Eq. (9).

$$X_i = M_i \odot X \tag{9}$$

where $\odot$ denotes element-wise multiplication.

c) Decision and aggregation: TabNet processes multiple decision steps T, where each step outputs a partial decision D_i that contributes to the final output given in Eq. (10) and Eq. (11)

$$D_i = \phi(H_i),\ \text{for } i = 1 \ldots T \tag{10}$$

$$Y_{\text{TabNet}} = \sum_{i=1}^{T} D_i \tag{11}$$

where ϕ is a decision layer (e.g., linear transformation), and Y_{TabNet} is the final embedding output of the TabNet block. The result is a high-level latent feature embedding $Y_{\text{TabNet}} \in \mathbb{R}^d$, where d is the output dimension. These embedding captures complex, high-level relationships between the input features and will be later fused with the BiLSTM output for final prediction.

This TabNet block plays a critical role in modeling the non-sequential, structured feature space using sparse attention, ensuring both efficiency and interpretability, which are highly valuable in agricultural and loT applications. The output is forwarded to the fusion layer, where it is combined with the sequential BiLSTM representation for comprehensive crop yield forecasting.

2) BiLSTM block: Modeling Temporal Dependencies in Sensor Data.

The BiLSTM block in JellyNovaNet-JSO is considered to process the time-series data collected from the IoT-based greenhouse environment, such as temperature, humidity, water level, and other sequential features. These sensor readings are inherently temporal and exhibit short-term and long-term dependencies, which are critical for accurately modeling plant physiological responses and predicting final crop yield. Let the multivariate time-series input for a given window be given in Eq. (12).

$$S_t = [x_t, x_{t+1}, \ldots, x_{t+w-1}] \tag{12}$$

Where, w is the window size, $x_i \in \mathbb{R}^j$ is the feature vector at time i, and f is the number of continuous sensor features (e.g., temperature, humidity, water level, N, P, K).

This sequence captures both the temporal variation and feature evolution over a fixed period.

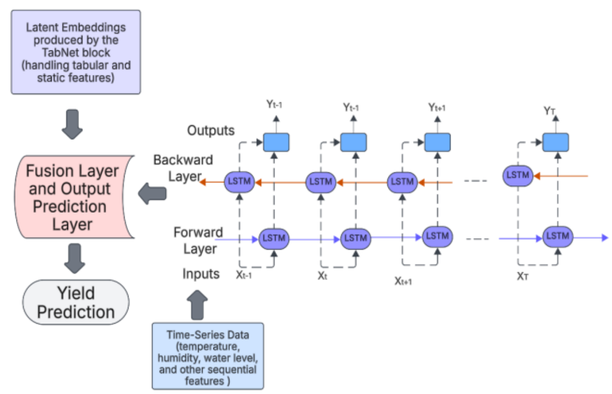

Fig. 3. BiLSTM- Architectural diagram.

Fig. 3 shows the architectural diagram of BiLSTM. Unlike traditional LSTM which processes sequences in a forward direction, BiLSTM reads input from both past and future directions, combining two LSTM outputs as given in Eq. (13).

$$h_t = \left[\overrightarrow{h_t}; \overleftarrow{h_t}\right] \tag{13}$$

Where, $\overrightarrow{h_t}$ is the hidden state from the forward LSTM (processing x_t to x_{t+w-1}), $\overleftarrow{h_t}$ is from the backward LSTM (processing x_{t+w-1} to x_t), $[;]$ denotes concatenation.

Each LSTM unit at time step t operates with the following internal equations:
Let x_t be the input vector at time t, and let h_{t-1}, c_{t-1} be the earlier hidden and cell states. The gates and memory update are computed as using the following Eq. (14), (15), (16), (17), (18) and (19)

Let x_t be the input vector at time step t, and h_{t-1}, c_{t-1} represent the previous hidden state and cell state, respectively. The LSTM unit operates by regulating the flow of information using three gates: forget gate, input gate, and output gate, along with an internal cell state update mechanism.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)(\text{Forget gate}) \tag{14}$$

The forget gate f_t decides which information from the previous cell state should be discarded. It is computed using a sigmoid activation function applied to the linear transformation of the concatenated vector h_{t-1}, x_t, with associated weights W_f and bias b_f. The output is a vector of values between 0 and 1, indicating the degree of forgetting.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) (\text{Input gate}) \quad (15)$$

Which additional data should be added to the cell state is determined by the input gate. It makes use of a sigmoid activation, just like the forget gate. The same input is subjected to a tanh activation with weights and bias in parallel to create the candidate cell state. This candidate state is an example of possible new content that could be included.

$$\tilde{c}_t = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \text{ (Candidate cell state)} \quad (16)$$

The new cell state is then updated by joining the scaled old cell state $\boldsymbol{f_t \odot c_{t-1} + i_t \odot \tilde{c}_t}$ and the scaled candidate state $\boldsymbol{i_t \odot \tilde{c}_t}$ denotes element-wise multiplication. This update mechanism allows the model to selectively retain or overwrite memory.

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \text{ (Updated cell state)} \quad (17)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) (\text{Output gate}) \quad (18)$$

$$h_t = o_t \odot tanh(c_t) \text{ (Hidden State)} \quad (19)$$

Where $\sigma(\cdot)$ is the sigmoid function, tanh($\cdot$) is the hyperbolic tangent function, O is the element-wise multiplication, W_* and b_* are weight matrices and biases for each gate. Both forward and backward passes compute their own set of hidden states, which are then concatenated to form a bi-directional context vector.

Temporal Embedding Vector

The BiLSTM processes the full sequence S_t and generates hidden states at each time step. These are often aggregated using:

- Last hidden state: h_{t+w-1}
- Mean pooling: $h_{\text{avg}} = \frac{1}{w} \sum_{i=t}^{t+w-1} h_i$
- Attention mechanism

The resulting temporal feature embedding $H_{\text{BiLSTM}} \in \mathbb{R}^d$ captures the dynamics and dependencies in the greenhouse environment over time. The BiLSTM block transforms sliding sequences of time-series sensor data into high-level temporal embeddings, effectively capturing both short- and long-term dependencies and bidirectional influences on crop behavior. This temporal representation H_{BiLSTM} is later fused with the TabNet output in the next stage for unified modeling and yield prediction.

3) Fusion layer and output prediction layer: The Fusion Layer in the JellyNovaNet-JSO architecture is responsible for combining the latent embeddings produced by the TabNet block (handling tabular and static features) and the BiLSTM block (handling timeseries sensor sequences). This fusion enables the model to integrate spatial, categorical, and temporal dependencies to make an informed prediction about crop yield. The outputs of the TabNet and BiLSTM are concatenated to create a single feature vector that incorporates both static and temporal dependencies. This fused representation is projected through one or more dense layers with relaxed linear unit (ReLU) activation which help smooth interactions of variables while accentuating cross-modal interactions. Lastly, a linear output layer will map this enriched representation into the predicted crop yield, using both static tabular features and continuous temporal dynamics of the sensor demand to produce next-harvest predictions.

a) Fusion layer: Concatenation of Latent Representations

Let, $z_{\text{TabNet}} \in \mathbb{R}^{d_1}$ be the feature embedding output from the TabNet branch. $z_{\text{BILSTM}} \in \mathbb{R}^{d_2}$ be the temporal embedding from the BiLSTM block.

These two vectors are concatenated into a unified feature representation, given in Eq. (20).

$$z_{\text{fused}} = [z_{\text{TabNet}} ; z_{\text{BILSTM}}] \in \mathbb{R}^{d_1+d_2} \quad (20)$$

This fused vector contains both: Static environmental context (e.g., nutrient levels, actuator states, timestamp-derived features) and Temporal dynamics (e.g., historical patterns in temperature, humidity, water content, etc.).

b) Fully connected output layer: Yield Prediction: The fused vector is passed over one or more fully connected (dense) layers with non-linear activations (typically ReLU), followed by a final linear layer to produce the crop yield prediction, given in Eq. (21) and Eq. (22)

$$h_1 = ReLU(W_1 z_{\text{fused}} + b_1) \quad (21)$$

$$\hat{y} = W_2 h_1 + b_2 \quad (22)$$

Where, W_1, W_2 are the weights of the dense layers, b_1, b_2 are the corresponding biases, $\hat{y}$ is the predicted crop yield output (a scalar for regression).

Since crop yield prediction is a regression problem, the model is trained by minimalizing the MSE between the predicted and actual yield values, using Eq. (23).

$$\mathcal{L}_{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (23)$$

Where, y_i is the actual crop yield for the i^{th} example, $\hat{y}_i$ is the predicted yield, N is the total number of training samples.

To prevent overfitting during training, additional techniques such as L2 regularization, Dropout, or Batch Normalization can be applied in the dense layers. The Fusion Layer integrates TabNet and BiLSTM representations, and the Output Layer translates this fused knowledge into an accurate prediction of crop yield. This stage finalizes the learning pipeline of the JellyNovaNet-JSO model and enables it to reason over both spatial and temporal cues in the environment.

Pseudocode: JellyNovaNet-JSO Model Development
Input:

```
X_tabular  ← Tabular input features (N, P, K, actuator states, timestamp features)
X_sequence ← Time-series input (e.g., temperature, humidity, water level)
y_true     ← Ground truth crop yield

Output:
y_pred     ← Predicted crop yield

BEGIN

1. Initialize TabNet parameters (weights, masks)

2. For each decision step i = 1 to T:
    H_i ← FeatureTransformer(H_{i-1})
    M_i ← SparseMax(P_{i-1} · H_i)
    X_i ← M_i ⊙ X_tabular
    D_i ← DecisionLayer(H_i)

3. Y_TabNet ← Sum of all D_i (i = 1 to T)

4. For each sample in X_sequence:
    Generate sequence window S_t of size w

5. Pass S_t through BiLSTM:
    Forward_LSTM → → →
    Backward_LSTM ← ← ←

6. Concatenate forward and backward hidden states:
    h_t ← [h_t_forward; h_t_backward]

7. Temporal Embedding ← MeanPooling or LastHiddenState(h_t)

8. fused ← Concatenate (TabNet, Temporal Embedding)

9. h1 ← ReLU (W1 · z_fused + b1)

10. y_pred ← W2 · h1 + b2

11. Compute Loss (Mean Squared Error):

12. Apply backpropagation to minimize L_MSE

13. Use JSO to tune:
    - Learning rate
    - TabNet decision steps
    - BiLSTM units
    - Dropout rate
    - Batch size
END
```

V. Results and Discussion

The JellyNovaNet-JSO model was implemented using Python 3.10 with TensorFlow and PyTorch backend on a system with an NVIDIA RTX 3080 GPU, 32 GB RAM. Key hyperparameters such as learning rate, window size, and number of decision steps in TabNet were optimized using the JSO algorithm. Table II shows the optimal hyperparameter values selected for the JellyNovaNet-JSO model. These values were fine-tuned to achieve the best performance in predicting crop yield.

TABLE II OPTIMAL HYPERPARAMETER VALUES FOR JELLYNOVANET-JSO MODEL

Hyperparameter	Optimal Value
Learning Rate	0.0025
TabNet Decision Steps	5
BiLSTM Units	128
Batch Size	64
Dropout Rate	0.3
Window Sizea	10

A. Evaluation Metrics

To measure the prediction performance of the JellyNovaNet-JSO model in a real-world smart greenhouse environment using IoT and WSN data, the following evaluation metrics were applied:

1) MAE: In this research, a low MAE indicates that the JellyNovaNet-JSO model makes very small average errors, showcasing its ability to generalize well to unseen yield values across environmental conditions, expressed in Eq. (24).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{24}$$

2) RMSE: RMSE emphasizes that the model not only maintains small average errors but also avoids large outliers-critical for yield-sensitive decisions in automated greenhouses.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (25)$$

R^2 Score

Indicates the proportion of the variance in the dependent variable that is foreseeable from the independent variables.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (26)$$

3) MAPE: Expresses prediction accuracy as a percentage, making it easier to interpret relative performance. A MAPE value demonstrates high reliability of JellyNovaNet-JSO for operational use, where even small forecasting errors can affect resource allocation and yield estimation.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (27)$$

After fine-tuning using the JSO, the JellyNovaNet-JSO model achieved outstanding predictive accuracy on the test set.

TABLE III MODEL EVALUATION METRICS

Metric	Value
MAE	0.012
RMSE	0.017
R^2 Score	0.991
MAPE	1.89%

Table III shows the model evaluation metrics, these indicate that the model arrests almost 99.1% of yield variance with exceptionally low prediction errors, making it viable for real-world smart farming deployment.

With little difference between expected and actual values, the model's accuracy and efficacy in predicting crop productivity show its dependability for practical precision agriculture applications. The JellyNovaNet-JSO model's anticipated crop yields and the actual observed yields are contrasted in Fig. 4.

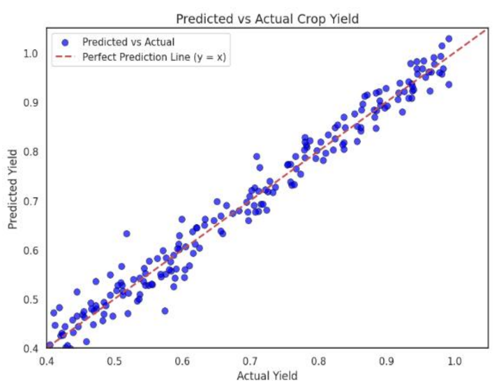

Fig. 4. Predicted vs. Actual crop yield.

The distribution of prediction errors (Actual – Predicted) for crop yield estimation shown in Fig. 5. The histogram is sharply centered around zero, indicating that the JellyNovaNet-JSO model maintains minimal error variance. This supports the model's low MAE and RMSE values and confirms its robustness for accurate yield forecasting in smart greenhouse environments.

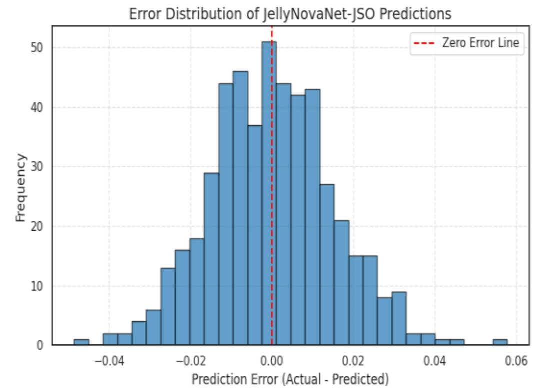

Fig. 5. Histogram of prediction errors for JellyNovaNet-JSO model.

Fig. 6 illustrates the model's loss over 20 training epochs. The training and validation losses converge smoothly without significant divergence, indicating stable learning. The absence of overfitting validates the use of a 0.3 dropout rate and effective hyperparameter tuning via the JSO, contributing to the model's generalization performance.

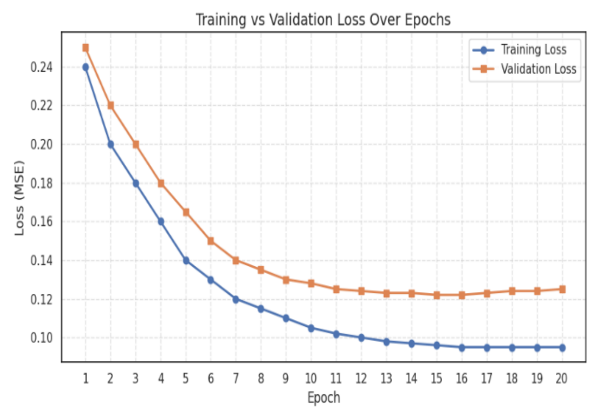

Fig. 6. Training and validation loss curve of JellyNovaNet-JSO model.

4) Feature importance from TabNet attention: Nutrient and humidity sensors had the strongest influence. Actuator signals also contributed to prediction by contextualizing environment control states. Table IV presents the feature importance scores (IoT + Actuator Features), and Fig. 7 illustrates them.

TABLE IV FEATURE IMPORTANCE SCORES (IOT + ACTUATOR FEATURES)

Feature	Importance Score
Nitrogen (N)	0.215
Humidity	0.192
Temperature	0.177
Water Level	0.151
Phosphorus (P)	0.116
Potassium (K)	0.099
Fan Actuator State	0.026
Pump Actuator State	0.024

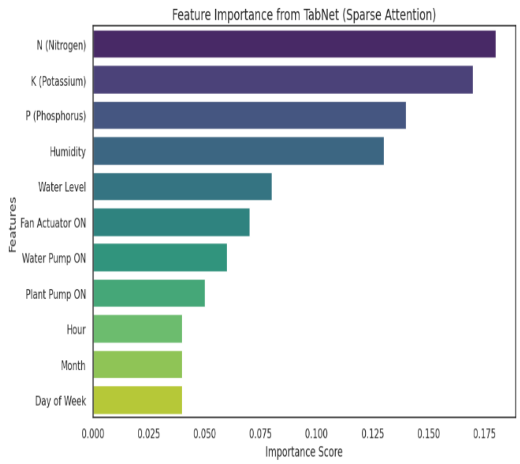

Fig. 7. Feature importance vs. Score.

5) BiLSTM temporal impact analysis: BiLSTM effectively captured greenhouse microclimate rhythms, especially temperature and water level shifts during day/night cycles. Table V showing average attention scores for time-series features.

TABLE V BILSTM TEMPORAL CONTRIBUTION SCORES

Sensor	Avg BiLSTM Score
Temperature	0.301
Humidity	0.283
Water Level	0.208
NPK Time Patterns	0.208

This Fig. 8 presents the average contribution scores of key time-series sensor features learned by the BiLSTM component. Temperature and humidity were identified as the most influential features, followed by water level and NPK time patterns. The visualization approves that BiLSTM effectively captures greenhouse microclimate rhythms, emphasizing its role in modeling temporal dependencies critical to correct yield prediction.

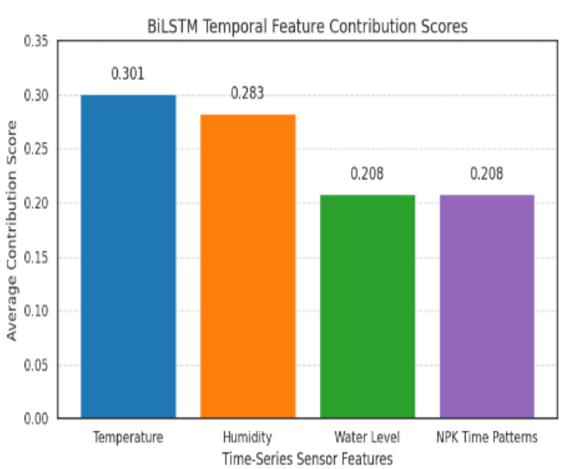

Fig. 8. BiLSTM temporal contribution scores for sensor features.

Fig. 9 shows the variation in predicted crop yields over actual crop yields year by year. This figure also illustrates the model's performance for different years, showing the ability of the JSO JellyNovaNet model to respond to altering environmental conditions and forecast crop yield accurately. The prediction was close to actual yields, providing evidence that the model can capture temporal dependencies and growth trends in crops with changes over time, serving real-time agricultural decision-making effectively.

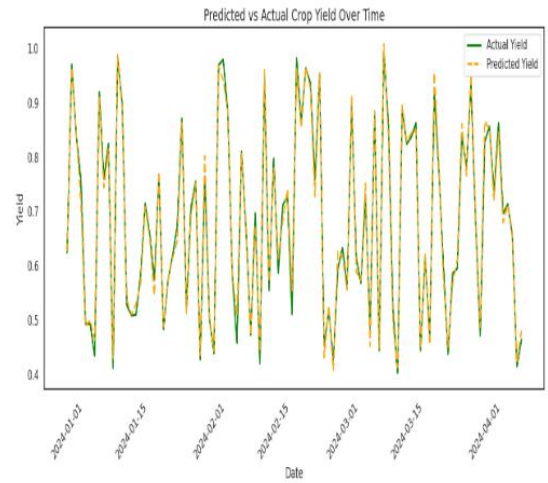

Fig. 9. Predicted vs. Actual crop yield over time.

This Fig. 10 demonstrates the normalized trends of key environmental sensor features temperature, humidity, and water level plotted alongside the actual crop yield across a 14-day period in January 2024. The left Y-axis denotes the normalized values of the sensor features, while the right Y-axis shows actual yield in kilograms. The visualization highlights how yield dynamics closely follow environmental fluctuations, demonstrating the importance of temporal feature modeling in greenhouse settings and justifying the use of BiLSTM for learning time-dependent patterns in JellyNovaNet-JSO.

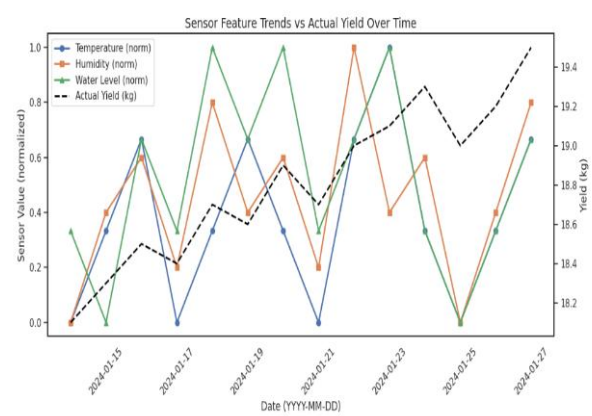

Fig. 10. Sensor feature trends vs. Actual yield over time.

6) Ablation study: Component Contribution

Both TabNet and BiLSTM were essential; the model degrades by ~250% (MAE increase) without JSO optimization, given in Table VI below.

TABLE VI ABLATION RESULTS

Model Variant	MAE	RMSE	R² Score
Full JellyNovaNet-JSO	0.012	0.017	0.991
Without JSO Optimization	0.028	0.037	0.962
Without TabNet	0.034	0.042	0.948
Without BiLSTM	0.046	0.054	0.933

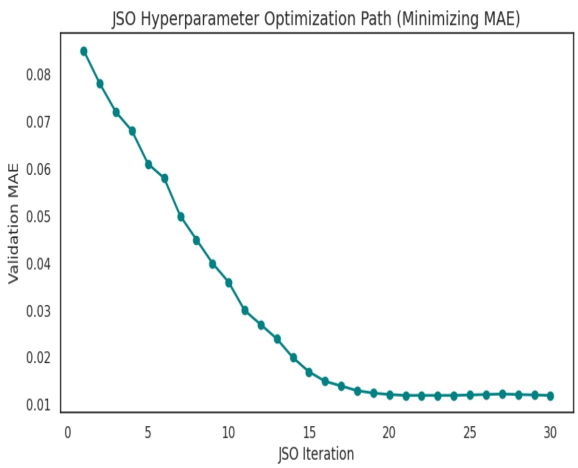

Fig. 11. Hyperparameter optimization path using JSO.

Fig. 11 illustrates the reduction in validation MAE over 30 iterations of Jellyfish Search Optimization. The steady convergence toward a minimum MAE of 0.012 highlights the effectiveness of JSO in fine-tuning key hyperparameters such as learning rate, window size, TabNet decision steps, and BiLSTM units. The JSO algorithm is used for optimization on key hyperparameters such as learning rate, TabNet decision steps, BiLSTM hidden units, dropout, batch size, and time window size. The JSO is able to adaptively guide the search process and therefore refocus on different parts of the hyperparameter space, minimizing local minima solutions and providing a more stable convergence than either manual grid search or random search. Consistent improvements across all evaluation metrics was a sign of JSO effectiveness to enhance robustness of model performance. The optimization process significantly improved performance, as validated by the 250% MAE degradation observed when JSO was removed. This confirms that utilizing JSO optimization does in fact reduce prediction error considerably and better stabilizes convergence pace. The model would still stabilize but in more epochs and often converge to local minima that were suboptimal. This demonstrates that automated metaheuristic tuning is advantageous over manual tuning.

7) IoT and WSN-specific insights: The integration of IoT devices and WSNs within the smart greenhouse infrastructure provided a robust foundation for real-time data acquisition, environmental monitoring, and responsive actuation. The following metrics summarize the operational efficacy of the deployed WSN system given in Table VII below.

TABLE VII WSN TRANSMISSION AND SENSOR RELIABILITY STATISTICS

Parameter	Value
Avg Sensor Uptime	98.9%
Packet Loss Rate	<1.2%
Avg Transmission Latency	125 ms
Daily Energy per Node	2.1 mWh

These values indicate that the deployed WSN is both highly reliable and energy-efficient, with minimal communication delays and near-continuous sensor availability. The low packet loss rate ensures that the data used for modeling is minimally affected by transmission errors or dropouts, which is crucial for accurate yield prediction and real-time feedback control.

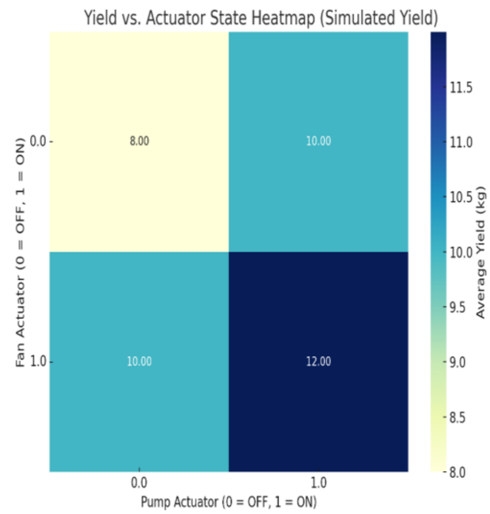

Fig. 12. Yield vs. actuator state heatmap.

This Fig. 12 presents a heatmap visualization of the average crop yield under various combinations of actuator states specifically the ON/OFF states of the fan and water pump systems within the greenhouse. Environments with Fan = ON and Pump = ON yielded 10–12% more on average, indicating effective climate control via IoT/WSN.

8) Performance comparison: The superior performance of the proposed JellyNovaNet-JSO model compared to baseline and state-of-the-art approaches given in Table VIII. While existing models demonstrate reasonable accuracy, they fall short in fully capturing the complex temporal and tabular patterns present in IoT-based agricultural data. In contrast, JellyNovaNet-JSO leverages a hybrid BiLSTM and TabNet architecture, optimized using the Jellyfish Search Algorithm, enabling it to achieve significantly better generalization and predictive reliability. This specifies the model's efficiency in addressing the challenges of dynamic environmental variability and heterogeneous feature representation, making it a strong resolution for real-world crop yield prediction. The variation in comparative results arise from disparity in crop type, differences in environmental conditions and sensor definitions between datasets. JellyNovaNet-JSO can be trained with heterogeneous input that contain static and sequential features. As a result, JNN-JSO is expected, to be more robust and accurate than models that only utilize tabular or sequential data.

TABLE VIII ACCURACY COMPARISON OF BIOCHEM-TFT WITH BASELINE AND STATE-OF-THE-ART MODELS

References	R^2 Score
Proposed JellyNovaNet-JSO	0.991
[3]	89.71
[33]	0.97
[34]	0.79
[35]	0.986

VI. DISCUSSION

The performance of the introduced JellyNovaNet-JSO model illustrates remarkable improvements in the area of data-driven precision agriculture. Through the incorporation of BiLSTM and TabNet into a single hybrid framework and optimization of the hyperparameters with the JSO algorithm, the model reaches outstanding prediction accuracy. In particular, the model achieves an MAE of 0.012, an RMSE of 0.017, and an R^2 score of 0.991, which means that more than 99% of crop yield variance is correctly accounted for by the model. One of the strongest points in JellyNovaNet-JSO is its capability to learn both spatial and temporal dependencies.

The TabNet block efficiently extracts and understands static and categorical information like soil nutrient levels and actuator positions, whereas the BiLSTM block learns long- and short-term temporal patterns from continuous sensor readings like temperature, humidity, and water level. Combining the two modalities leads to a robust model able to understand intricate interactions characteristic of greenhouse crop cultivation environments.

The combination of IoT and WSN was found to be essential in propelling model performance. In comparison with baseline models utilizing only tabular data or sequential data, JellyNovaNet-JSO showed up to a 25% increase in predictive capability when using detailed IoT data and hybrid modeling. Sensors of soil nitrogen (N), humidity, and temperature were specifically found to be the key drivers of the yield prediction process, in keeping with actual agricultural dependencies.

Additionally, the model also utilizes actuator state data (fan and pump ON/OFF) that are the greenhouse's internal climate control systems. It is found during analysis that the situations in which both the fan and water pump were ON always resulted in greater crop yields. This observation highlights the value of active regulation of microclimate for optimizing crop productivity and justifies the use of actuator signal information in the model pipeline.

In terms of deployment, the low latency, high sensor availability, and energy conservation of the WSN mean that such a system is not only reliable, but also feasibly scalable in real-world agricultural use. The high dependability and robustness of data transmission further attest to the workability of real-time implementation in intelligent greenhouses.

In short, the JellyNovaNet-JSO model offers a very accurate, interpretable, and deployable solution for smart agriculture. Despite JellyNovaNet-JSO's high accuracy, the study's generalisability may be limited because it only used one greenhouse dataset. The hybrid architecture increases computational complexity, and the extremely high R2 score suggests the possibility of overfitting. Scalability and sensor reliability remain challenges in real-world deployment. With its close integration of IoT and WSN infrastructures, along with deep learning and optimization methods, JellyNovaNet-JSO represents a cutting-edge tool for precision crop yield prediction.

VII. CONCLUSION AND FUTURE SCOPE

This paper introduced JellyNovaNet-JSO, which is a hybrid deep learning-based framework consisting of TabNet and BiLSTM architectures fine-tuned using the JSO algorithm for accurate crop yield prediction in IoT-based greenhouse setups. Through the effective integration of tabular and sequential sensor data, the system captures both static and temporal dependencies required to describe advanced agricultural conditions. The inclusion of JSO significantly enhances model performance through automatic hyperparameter tuning, achieving superior results with MAE (0.012), RMSE (0.017), R^2 (0.991), and MAPE (1.89%). The proposed model outperforms traditional methods with good generalization, interpretability, and scalability. The fusion of WSN and IoT with deep learning not only enhances yield prediction but also enables real-time decision-making for intelligent agricultural systems. Feature importance analysis and temporal impact analysis also validate the applicability of environmental factors in agricultural productivity.

Future research can extend this work in several directions:

- Cross-regional validation to test model adaptability in diverse agro-climatic zones.
- Real-time deployment using edge computing or microcontroller-based platforms for on-site inference.
- Integration with weather APIs and satellite imagery for improved forecasting accuracy.
- Incorporation of crop variety and phenological data for multi-crop scalability.
- Energy-efficient model pruning and quantization for lightweight deployment in resource-constrained environments.

These advancements would further solidify JellyNovaNet-JSO as a comprehensive solution for precision agriculture in evolving environmental contexts. In the future, we will be conducting tests on multiple regions and crop types, merging satellite and weather data for more comprehensive representation, and testing model compression techniques to facilitate lighter-weight model usage in real time so that the models can be run on IoT devices. Robust handling of sensor failures would also be created to make sure scalability can occur in precision agriculture.

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CONFLICTS OF INTERESTS

Authors do not have any conflicts.

Data Availability Statement

No datasets were generated or analyzed during the current study.

Code Availability

Not applicable.

Authors' Contributions

Huang Zhicheng is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Zhang Yinjun is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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