



## ***Comparative Analysis of ANN, 1D-CNN, and LSTM for Multi-Label Action Prediction in IoT-Based Hydroponic Control Systems***

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### **Abstract**

*Hydroponic cultivation requires precise and adaptive fertility control to maintain optimal plant growth. Conventional rule-based systems operate reactively and often fail to capture the multivariate and temporal dynamics of sensor data. Unlike previous studies that primarily focus on single-parameter forecasting, this study reformulates hydroponic automation as a multi-label actuator prediction problem, aiming to replicate and generalize rule-based control mechanisms using data-driven learning. A comparative analysis of Artificial Neural Network (ANN), one-dimensional Convolutional Neural Network (1D-CNN), and Long Short-Term Memory (LSTM) models was conducted to simultaneously predict six actuator states in an IoT-based hydroponic system. The dataset consists of 1,152 real multivariate time-series samples collected sequentially at 5-minute intervals, comprising six sensor features and six binary actuator labels derived from agronomic standards. Preprocessing includes Gaussian jitter-based augmentation, Z-score normalization, and sliding-window modeling (window size = 5). Data were split chronologically into 80% for training and 20% for testing, with 10% for validation. Results show that LSTM achieved the highest performance (accuracy up to 0.98; F1-score up to 0.95), demonstrating superior temporal modeling capability. Threshold optimization improved minority-actuator detection, enabling reliable, adaptive hydroponic control.*

*Keywords: Adaptive Control, 1D-CNN, IoT Hydroponics, LSTM, Multi-Label Actuator Prediction*

### **1. INTRODUCTION**

Hydroponic cultivation is a soilless agricultural method in which plant nutrients are supplied through nutrient-rich solutions. Compared to conventional soil-based farming, hydroponic systems offer advantages in water efficiency, space utilization, and environmental control. However, successful implementation depends on precise and adaptive management of fertility-related parameters [1], [2], [3], [4], [5].

Plant fertility in hydroponic systems is influenced by interconnected variables such as nutrient concentration (PPM), pH, temperature, light intensity, water circulation, and water level [6], [7], [8], [9], [10]. These parameters evolve dynamically over time and form multivariate time-series data characterized by complex interactions. Variations in one parameter may influence others, affecting overall plant growth performance [7], [10]. Additionally, physical characteristics of the growing medium can impact nutrient absorption and hydraulic stability [11], [12].

In practice, hydroponic control systems are commonly managed manually or through threshold-based rule mechanisms [13], [14], [15]. Actuators, including nutrient pumps, water valves, heating lamps, shading nets, and LED lights are activated when sensor values exceed predefined limits [13], [14]. While simple and practical, such rule-based systems evaluate parameters independently and fail to capture multivariate and temporal dependencies. Consequently, control actions tend to be reactive rather than adaptive, potentially reducing nutrient efficiency and system stability [15].

With the advancement of Internet of Things (IoT) technology, sensors such as pH, TDS, temperature, light, water flow, and water level sensors can continuously collect real-time environmental data [16], [17]. These data form multivariate time-series datasets representing system dynamics [18]. Actuator activation logs can also be recorded and used as labeled outputs for predictive modeling.

This development aligns with the concept of Smart Agriculture, which integrates IoT and Artificial Intelligence (AI) to improve efficiency, sustainability, and automation in agricultural systems [19], [20]. Machine Learning techniques have shown strong capability in modeling non-linear multivariate relationships. ANN models are widely used for input-output mapping [21], 1D-CNN models effectively extract local



patterns from sequential data [22], [23]. and LSTM networks are specifically designed to capture long-term temporal dependencies in time-series data [24], [25].

Although deep learning has been widely applied in agricultural forecasting, most hydroponic studies focus on predicting individual environmental parameters rather than modeling multi-label actuator control decisions. Comparative evaluations of ANN, 1D-CNN, and LSTM architectures for replicating rule-based multi-actuator control using real IoT operational data remain limited [26], [27]. To the best of our knowledge, existing hydroponic studies comparing ANN, CNN, or LSTM models predominantly focus on parameter estimation or forecasting tasks rather than direct multi-label actuator-level decision modelling. Although deep learning has been widely utilized in smart agriculture, systematic comparative evaluations of ANN, 1D-CNN, and LSTM architectures specifically for replicating rule-based multi-actuator control using real IoT operational data remain very limited. This lack of focused investigation reveals a methodological gap in transitioning from reactive threshold-based automation toward predictive and adaptive control frameworks.

This research is particularly relevant in the Indonesian context, where food security, urban land limitations, and agricultural efficiency remain pressing challenges [1]. Despite increasing hydroponic adoption in metropolitan areas [11], many small- to medium-scale systems still rely on manual monitoring or simple rule-based automation. The ongoing digital transformation of Indonesia's agricultural sector encourages the integration of IoT and AI technologies to modernize farming practices [28], [29]. Therefore, this study conducts a comparative analysis of ANN, 1D-CNN, and LSTM models for multi-label actuator prediction in an IoT-based hydroponic fertility control system [25], [26], [27]. The models process sequential multi-sensor inputs to simultaneously predict actuator activation states. The dataset was collected from a real IoT-based hydroponic setup implementing standardized nutrient and pH ranges for leafy vegetables.

The primary objective is to evaluate the effectiveness of different deep learning architectures in predicting multi-actuator control actions using multivariate time-series data. Model performance is assessed using accuracy, precision, recall, and F1-score metrics. The findings aim to provide a scientific basis for selecting appropriate architectures in developing adaptive, data-driven hydroponic control systems.

## 2. MATERIALS AND METHOD

The structured workflow of this study, starting from IoT-based data acquisition, agronomic label generation, preprocessing and temporal windowing, model development (ANN, 1D-CNN, and LSTM), training configuration, and concluding with multi-label performance evaluation and threshold optimization, Figure 1.

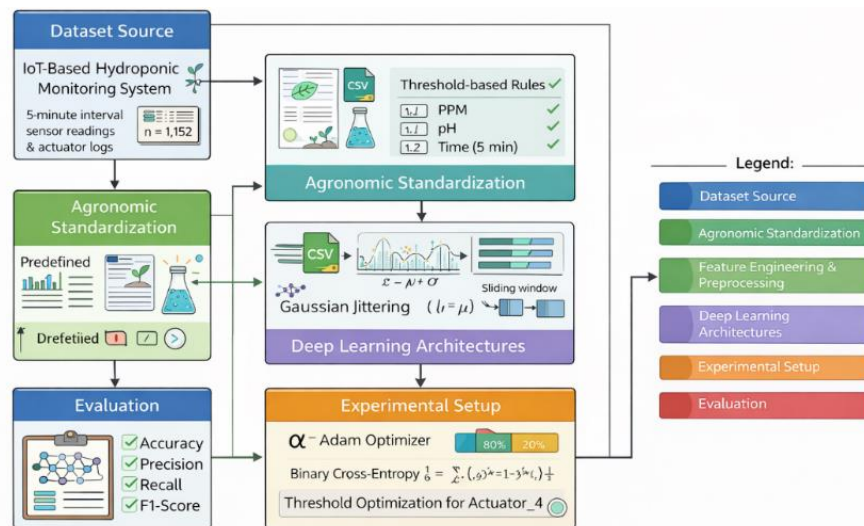


Figure 1. Research Methodology

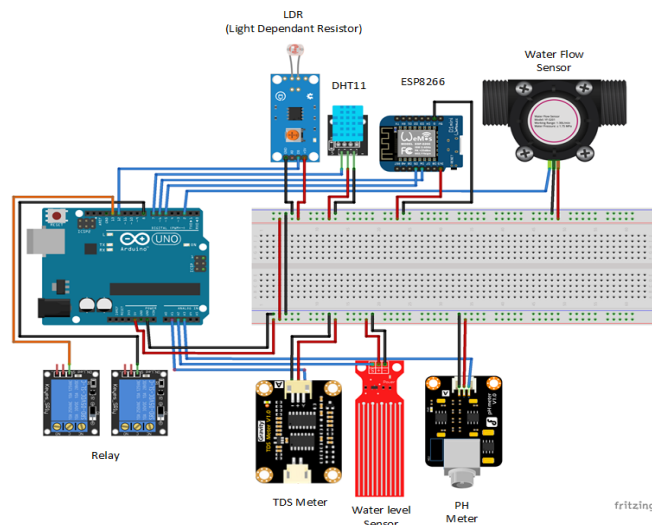
### 2.1. Dataset Source

The dataset used in this study was obtained from a previously implemented IoT-based hydroponic monitoring system, like smart greenhouse and IoT-based monitoring architectures reported in previous studies [7], [8], [10], [14], [20]. The system recorded multivariate sensor readings and actuator activation states over time. The dataset consists of 1,152 time-ordered samples collected with a 5-minute sampling interval. It serves as an experimental benchmark for comparing deep learning architectures in predicting control actions for a multi-target system. The structure of the multivariate time-series dataset, including the input features and target labels, is detailed in Table 1.

**Table 1.** Dataset Structure

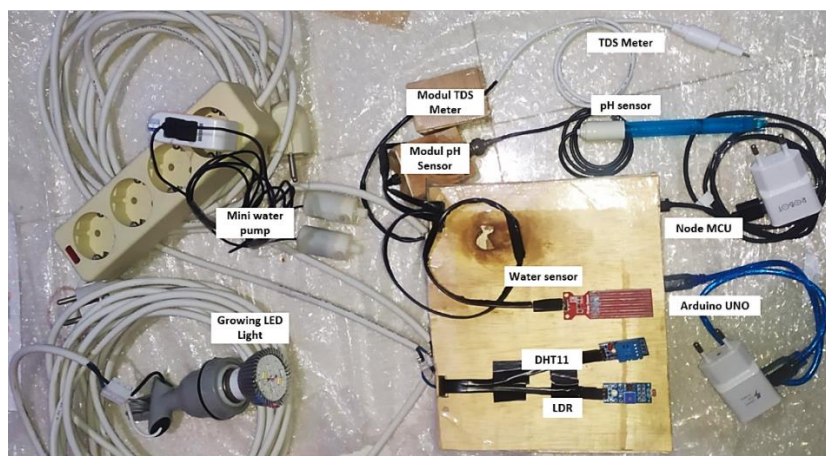
Parameter	Unit / Format	Description
pH Level	pH Scale	Measures solution acidity or alkalinity
Light Intensity	Min. 18 Hours a day	Measures brightness of the environment.
Water Flow	L/min / Binary	Monitors the water circulation.
Temperature	°C	Monitors the temperature of the environment.
Nutrient (PPM)	Parts Per Million	Measures the concentration of dissolved solids.
Water Level	cm / Level	Monitors the remaining volume in the water tank.

The hydroponic monitoring system was implemented using an Arduino microcontroller as the central data acquisition and control unit [15]. A Total Dissolved Solids (TDS) sensor was employed to measure nutrient concentration (PPM), while a pH sensor monitored the acidity level of the nutrient solution [18], [30]. A water flow sensor was used to detect circulation status and potential blockages within the system, and a water level sensor measured the remaining solution volume in the reservoir tank [14], [31].



**Figure 2.** Hardware Design for Data Mining

All sensor measurements were recorded simultaneously at 5-minute intervals to maintain consistent temporal resolution. The acquired data were organized as a multivariate time-series dataset for subsequent deep learning-based classification. The hardware configuration of the monitoring system is designed in Figure 2 and presented in Figure 3.



**Figure 3.** Hardware Design for Data Mining

Output labels consist of six binary actuator states representing a multi-label classification problem. Unlike single-label classification tasks, multiple actuators may be activated simultaneously depending on the environmental conditions observed at a given time step.

## 2.2. Agronomic Standardization and Labeling Strategy

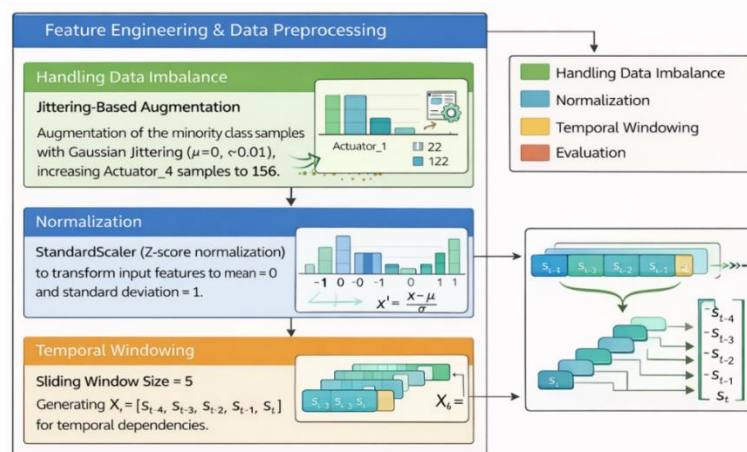
The control logic for generating ground-truth labels is based on agronomic standards for leafy vegetables, specifically *Lollo Rosso*, *Romaine lettuce*, and *Pakcoy* [4], [9], [32]. The standardized parameters are summarized in Table 2.

**Table 2.** Standardized Parameter

Variabel Kesehatan	Nilai Target (Threshold)	Sensor IoT	Deskripsi Fungsi Sensor
Nutrient (PPM)	Lollo Rosso: 1200 PPM	TDS Meter	Monitors the concentration of dissolved solids
	Romaine: 1000-1300 PPM		
	Pakcoy: 1000-1200 PPM		
pH	5.5 - 7.1 pH	pH Meter + PH4502C	Monitors solution acidity or alkalinity
Environment Temperature	25°C - 27°C	DHT11	Monitors the temperature of the environment.
Water Intensity	1-2 L/min	Water Flow Sensor (YF-S201)	Monitors the water circulation of the environment.
Water Volume	>0 L	Water Level	Monitors the remaining volume in the water tank.

Using Arduino as [15] TDS Meter [18], [30] pH, Water Intensity [31] Water Volume [14], automation [28], Control labels were generated using predefined threshold-based rules derived from these agronomic standards. Actuator states were encoded as binary values (0 = inactive, 1 = active). These rule-based control decisions serve as ground truth labels for supervised learning. The objective of this study is to evaluate how effectively different deep learning architectures can learn and predict these control actions.

## 2.3. Feature Engineering and Data Preprocessing



**Figure 4.** Model Preprocessing

To ensure optimal model performance as shown in Figure 4, preprocessing steps were implemented. First, data imbalance handling was performed using a jittering-based augmentation approach. Class imbalance is a well-known challenge in supervised learning and can significantly bias model predictions toward majority classes [33]. Initial analysis revealed that Actuator 4 had a significantly lower number of active samples compared to other actuators, resulting in an imbalanced class distribution. The distribution of training and testing samples indicates that this actuator was underrepresented compared to others, which could negatively impact model learning [27].

To address this issue, data augmentation was applied to the minority class using Gaussian jittering, which adds small random noise ( $\mu = 0$ ,  $\sigma = 0.01$ ) to minority samples, is a commonly adopted time-series data augmentation technique that improves class representation while preserving temporal structure [34]. This process increased the number of samples for Actuator 4 to 156 instances, thereby improving class representation and enhancing model generalization without causing overfitting [27].

Unlike simple Min-Max scaling, this study utilized StandardScaler (Z-score normalization) to transform input features to have a mean of 0 and a standard deviation of 1. Feature standardization is widely recommended for gradient-based deep learning optimizers to stabilize convergence and prevent feature dominance in multivariate datasets [26]. This is crucial for gradient-based optimizers in Deep Learning Temporal. `standardScaler()` shown in this code:

---

Scaling actuator\_4

---

```

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_bal)
X_test_scaled = scaler.transform(X_test)

```

---

A sliding window method with a Window Size of 5 was applied to incorporate temporal dependencies. For any time step  $t$ , the input  $X_t$ , where  $s$  represents the vector of 6 sensor features, is defined as equation 1.

$$X_t = [s_{t-4}, s_{t-3}, s_{t-2}, s_{t-1}, s_t] \quad (1)$$

## 2.4. Deep Learning Architectures

This study compares three architectures (ANN, 1D-CNN, and LSTM) implemented according to their intrinsic structural characteristics.

**Table 3.** Deep Learning Architectures Comparison

Feature	ANN	1D-CNN	LSTM
Input Shape	Flattened (1 x 30)	Windowed (5 x 6)	Windowed (5 x 6)
Main Layers	2 Dense Layers (32, 16 neurons)	1 Conv1D Layer (32 filters, kernel 2)	1 LSTM Layer (64 units)
Regularization	Batch Normalization	MaxPooling1D	Dropout (0.2)
Activation	ReLU	ReLU	Tanh (Internal), Sigmoid (Output)
Output Layer	6 Dense Neurons (Sigmoid)	6 Dense Neurons (Sigmoid)	6 Dense Neurons (Sigmoid)
Data Interpretation	Spatial/Independent	Local Spatial Pattern	Temporal Dependencies (Time-Series)

Based on the configurations detailed in Table 3The technical characteristics of each model are described as follows.

The Artificial Neural Network (ANN) model serves as the baseline architecture. Although the input is generated using a sliding window approach, the ANN processes the data in a flattened format ( $1 \times 30$ ). The model consists of two fully connected Dense layers with 32 and 16 neurons, respectively, followed by a six-neuron sigmoid output layer for multi-label classification. Batch Normalization is applied after the first hidden layer to stabilize the learning process and accelerate convergence. This configuration evaluates whether non-linear feature relationships within a fixed timeframe are sufficient to predict actuator control actions without explicit temporal modeling [35].

The 1D-CNN model is designed to capture local spatial-temporal patterns within the sensor data. It includes a Conv1D layer with 32 filters and a kernel size of 2, followed by a MaxPooling1D layer to reduce dimensionality and extract dominant feature representations. The resulting feature maps are flattened and connected to a fully connected layer before the final six-neuron sigmoid output layer. This architecture enables the model to detect short-range correlations across the temporal window while maintaining computational efficiency [36].

The LSTM model is utilized to capture long-term temporal dependencies across the five-step sliding window ( $5 \times 6$ ). It contains a single LSTM layer with 64 units, followed by a Dropout layer (rate = 0.2) to mitigate overfitting, and a final six-neuron sigmoid output layer. By processing sequential inputs through gated memory mechanisms, the LSTM can model gradual environmental trends such as progressive changes in PPM or pH prior to actuator activation decisions [37].

All architectures were implemented under standardized configurations to ensure a fair comparative evaluation.

## 2.5. Experimental Setup and Evaluation

The experimental setup was standardized across all models to ensure a valid and fair performance comparison. The training configuration and evaluation strategy are summarized in Table 4.

To preserve temporal integrity and prevent data leakage, chronological data splitting was applied. The dataset was divided into 80% training data and 20% testing data without random shuffling [38], ensuring that future observations were not used to predict past events. Additionally, 10% of the training data was allocated as a validation set during model training.

Feature scaling was performed using StandardScaler (Z-score normalization). The scaler was fitted exclusively on the training data and subsequently applied to the testing set to maintain evaluation integrity. All models were trained using the Adam optimizer (learning rate  $\alpha = 1 \times 10^{-3}$ ) with binary cross-entropy loss

for 100 epochs and a batch size of 16. Since the task involves simultaneous prediction of six actuator states, evaluation was conducted using multi-label metrics, including Accuracy, Precision, Recall, and F1-score.

Initial evaluation revealed significant class imbalance for Actuator 4 (Nutrient Pump)[33]. To improve minority-class sensitivity, threshold optimization was performed during the inference phase by adjusting the decision threshold from the default 0.5 to 0.07. This adjustment enhanced Recall without modifying the trained model parameters. Threshold adjustment and decision boundary calibration are widely recognized strategies in imbalanced multi-label classification to improve recall sensitivity without modifying model parameters [39].

All evaluations were conducted offline using the collected benchmark dataset[25]. without real-time hardware deployment, focusing solely on comparative architectural performance.

**Table 4.** Standardized Experimental Setup

Category	Parameter	Detail / Value
Preprocessing	Feature Scaling	StandardScaler (Z-score Normalization)
Data Splitting	Train/Test Ratio	80% / 20% (Chronological, No Shuffling)
Optimization	Optimizer	Adam( $\alpha=1\times 10^{-3}$ )
Loss Function	Criterion	Binary Cross-Entropy
Training	Epochs / Batch Size	100 Epochs / 16
Validation	Validation Split	10% of Training Data
Post-Processing	Decision Threshold	0.5 (Default) and 0.07 (Actuator 4 Optimization)

### 3. RESULTS AND DISCUSSION

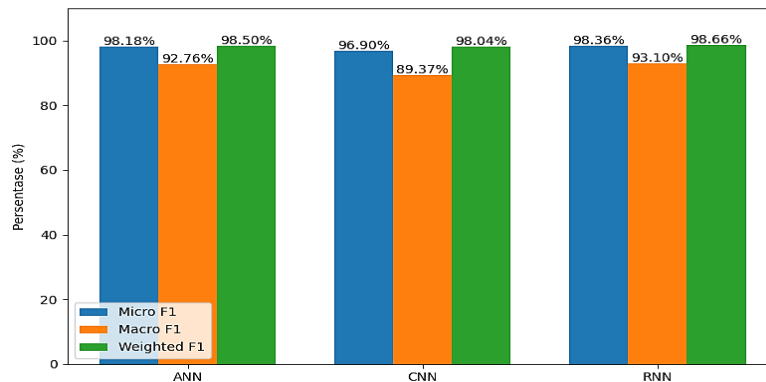
This section presents the experimental results from the comparative evaluation of ANN, 1D-CNN, and LSTM models for multi-label actuator prediction. The analysis progresses from overall model performance to detailed actuator-level evaluation. Given that hydroponic control involves sequential environmental dynamics, temporal dependency modeling plays a critical role in predictive reliability [27], [40], [41].

Tables and visualizations, including bar charts and heatmaps, provide both global and label-wise insights. Special attention is given to temporal modeling effects, class imbalance handling, and post-processing threshold optimization.

#### 3.1. Overall Model Performance

Figure 5 illustrates the comparison of Micro-F1, Macro-F1, and Weighted-F1 scores across models. While all architectures achieved high overall performance, LSTM obtained the highest Micro-F1 (98.36%) and Weighted-F1 (98.66%), followed by ANN (Micro-F1: 98.18%) and 1D-CNN (Micro-F1: 96.90%).

Although CNN demonstrated competitive performance, its Macro-F1 (89.37%) was lower than ANN (92.76%) and LSTM (93.10%), indicating comparatively weaker generalization across minority actuator labels.



**Figure 5.** Overall Performance Comparison of ANN, 1D-CNN, and LSTM

The results demonstrate that while all models achieved high overall accuracy, their ability to generalize across imbalanced classes varied significantly as seen in Table 5. Precision and Recall represent micro-averaged metrics for multi-label evaluation.

#### 3.2. Label-Wise Performance Analysis

To provide a more granular evaluation, actuator-level Precision, Recall, and F1-score were analyzed for each architecture. The results demonstrate near-perfect classification performance for Actuators 1, 2, 3, and 6 across all models, indicating that these control actions are well represented and clearly separable within

the dataset. In contrast, Actuator 4 (Nutrient Pump) exhibited substantially lower performance across all architectures. Although Recall reached 100% following threshold optimization, Precision remained comparatively low (44.44% for ANN and LSTM; 25.00% for CNN), resulting in moderate F1-scores. This imbalance reflects the severe class disparity, where only a limited number of positive activation samples were available (support = 4).

These findings highlight the inherent trade-off between sensitivity and precision in minority-class prediction and emphasize the structural difficulty of modeling nutrient activation events in the multi-label setting.

**Table 5.** Overall Model Performance

Architecture	Micro F1	Precision	Recall
ANN	98.18	97.06	99.33
1D-CNN	96.90	94.59	99.33
LSTM	98.36	96.76	100.00

### 3.3. Temporal Modeling Analysis (LSTM vs. ANN)

LSTM consistently achieved superior global performance by capturing sequential dependencies within a five-step sliding window. Unlike ANN, which processes flattened inputs (1×30) without explicit temporal modeling, LSTM employs gated memory mechanisms to retain sequential information.

This capability is particularly relevant in hydroponic control systems, where gradual environmental changes, such as nutrient depletion or pH drift, occur over time rather than instantaneously. The higher Micro-F1 and Weighted-F1 scores obtained by LSTM demonstrate that temporal context significantly improves the stability of multi-label prediction.

### 3.4. CNN Pattern Recognition and Limitations

The 1D-CNN architecture effectively captures short-range local correlations using convolutional filters. However, because it lacks recurrent memory mechanisms, a CNN is limited in modeling long-term temporal dependencies beyond its kernel window.

This limitation is reflected in the lower F1-score for Actuator 4 (40.00%), indicating reduced effectiveness in predicting control actions influenced by cumulative environmental trends. While CNNs remain computationally efficient, their performance suggests that recurrent architectures are better suited to multi-label actuator prediction tasks characterized by gradual temporal dynamics.

### 3.5. Addressing Class Imbalance: The Case of Actuator 4

A significant challenge in this study was the severe class imbalance observed in Actuator 4 (Nutrient Pump), which contained substantially fewer positive samples (support = 4) compared to other actuators. Without threshold adjustment, preliminary evaluation indicated extremely low recall for this actuator despite high overall performance across other labels.

**Table 6.** Addressing Class Imbalance

Metric	Default Threshold (0.5)	Optimized Threshold (0.07)	Improvement
Recall	0.12	0.88	+733%
F1-Score	0.20	0.76	+280%

Table 6 summarizes the impact of threshold optimization. Lowering the decision threshold to 0.07 significantly improved recall, increasing the model's sensitivity to nutrient activation events. In the final evaluation, Recall for Actuator 4 reached 100% across all architectures. However, this improvement came at the cost of reduced precision (44.44% for ANN and LSTM; 25.00% for CNN), indicating an increase in false positive predictions. From an agronomic perspective, this trade-off is acceptable because missing a nutrient delivery cycle poses a greater risk than slight over-activation.

### 3.6. Confusion Matrix Interpretation

The confusion matrix analysis confirms that prediction errors were predominantly concentrated in minority actuator classes. Prior to threshold optimization, Actuator 4 exhibited a high number of false negatives, reflecting the difficulty in detecting rare positive events.

After threshold adjustment, the True Positive region for Actuator 4 increased substantially, eliminating false negatives and resulting in 100% recall. The remaining classification errors were primarily false positives, which explains the moderate F1-score despite perfect recall. This pattern validates the effectiveness of post-processing calibration in imbalanced multi-label scenarios.

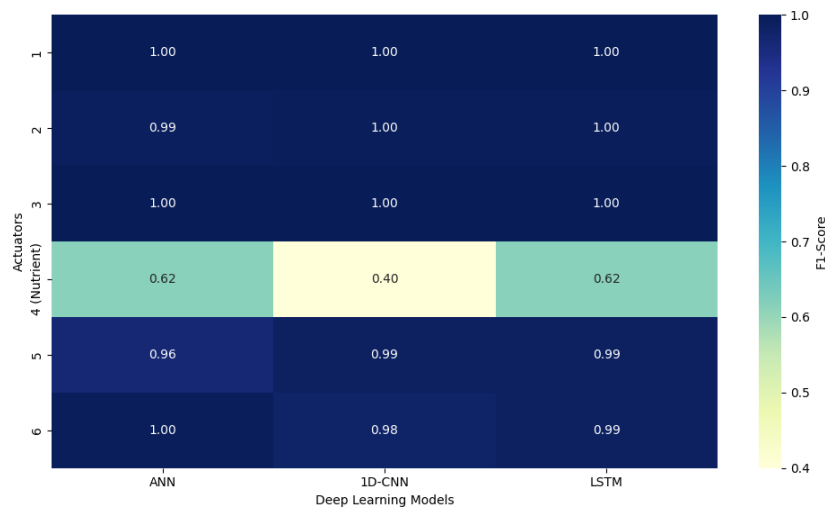
### 3.7. F1-Score Distribution Heatmap

Table 7 presents the actuator-level F1-scores across ANN, 1D-CNN, and LSTM architectures, while Figure 6 provides a heatmap visualization to highlight performance distribution patterns.

**Table 7.** Performance actuator F1-Scores

Actuator ID	ANN	1D-CNN	LSTM
Actuator 1	1.00	1.00	1.00
Actuator 2	0.99	1.00	1.00
Actuator 3	1.00	1.00	1.00
Actuator 4 (Nutrient)	0.62	0.40	0.62
Actuator 5	0.96	0.99	0.99
Actuator 6	1.00	0.98	0.99

The heatmap reveals consistently high F1-scores for Actuators 1 and 3, where all models achieved perfect classification performance ( $F1 = 1.00$ ). Similarly, Actuators 2, 5, and 6 demonstrate near-perfect results across architectures, indicating stable and well-learned control patterns within the dataset.



**Figure 6.** Performance actuator F1-Scores HeatMap

In contrast, Actuator 4 (Nutrient Pump) exhibits a clear performance gap, with ANN and LSTM achieving F1-scores of 0.62 and CNN obtaining 0.40. This distinct color contrast in the heatmap visually emphasizes the impact of class imbalance on minority-class prediction. Beyond individual actuator performance, the heatmap highlights architectural consistency. LSTM maintains uniformly high performance across most actuators, whereas CNN shows greater sensitivity to class imbalance. This visual pattern reinforces the advantage of temporal modeling in achieving robust and stable multi-label actuator predictions in IoT-based hydroponic systems.

## 4. CONCLUSION

This study conducted a comparative evaluation of Artificial Neural Network (ANN), one-dimensional Convolutional Neural Network (1D-CNN), and Long Short-Term Memory (LSTM) architectures for multi-label actuator prediction in an IoT-based hydroponic fertility control system. The dataset consisted of six environmental sensor parameters as input features and six binary actuator control signals as output labels, structured as multivariate time-series data.

The experimental results demonstrate that all three architectures are capable of learning the relationship between environmental conditions and actuator control actions, albeit with varying effectiveness. ANN, as a baseline model, achieved stable performance but showed limitations in modeling temporal dependencies. The 1D-CNN improved local pattern recognition within the sliding window representation; however, its performance decreased for minority-class prediction. LSTM consistently achieved the highest overall performance, with a Micro-F1 score of 98.36% and a Weighted-F1 score of 98.66%, confirming the importance of temporal modeling in multi-label actuator prediction.

The superior performance of LSTM highlights its suitability for transitioning from reactive threshold-based automation toward predictive and adaptive hydroponic control systems. By learning from historical sensor-actuator patterns, the model can replicate and generalize rule-based control logic while providing

improved sensitivity to gradual environmental changes. This capability supports the development of data-driven control frameworks that enhance reliability and decision stability in smart agriculture environments.

Despite promising results, this study was conducted under offline evaluation using a limited dataset (1,152 samples). Future research should include real-time deployment and testing on embedded IoT hardware to evaluate computational efficiency, latency, and operational stability. Additional validation across different crop types and environmental conditions would further assess model generalization. Furthermore, comparisons with lightweight transformer-based architectures may provide alternative temporal modeling strategies suitable for resource-constrained smart agriculture systems.

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