國立台北大學資訊工程學系專題報告

環境永續整合監測、分析、與預測

Integrated Monitoring, Analysis, and Prediction of Environmental Sustainability

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專題編號:PRJ-NTPUCSIE-113-012
執行期間:2024 年 09 月 至 2025 年 06 月

Abstract*—This study presents the development of an integrated environmental monitoring and prediction system based on LoRa-IoT technology and deep learning, aimed at real-time assessment of air and water quality around Mind Lake at National Taipei University. Utilizing multiple Arduino-based sensor nodes, key environmental parameters—including PM2.5, pH, dissolved oxygen, conductivity, and water temperature—were continuously collected and transmitted over long distances via a LoRaWAN network. A backend system built with ExpressJS handles data processing and storage, while several deep learning models, including Gated Recurrent Unit (GRU), CNN-GRU, Long Short-Term Memory (LSTM), CNN-LSTM,Transformer, and Ensemble(Stacking) are employed for time-series predictions to forecast environmental changes. The resulting data are visualized in real time on a bilingual (Chinese-English) web interface, offering transparent access to environmental conditions for both the campus community and relevant stakeholders. By combining IoT-based sensing with deep learning prediction, this system not only enhances environmental awareness but also provides a scalable and cost-effective solution for supporting data-driven environmental management and decision-making in academic settings.

***Keywords*—Environmental Monitoring, Deep Learning, IoT(Internet of Things), LoRaWAN, Water Quality Prediction, Ensemble Learning**

I. INTRODUCTION

Environmental sustainability is a pressing global issue, especially in urban and institutional settings where human activity closely interacts with ecosystems. University campuses, as noted by [1], are vital not only for reducing environmental impact but also for offering experiential learning opportunities. The National Taipei University (NTPU) campus, centered around the biodiverse Mind Lake, exemplifies such a setting. While considered one of Taiwan’s “healthy campuses,” anecdotal reports and rising biodiversity (ducks, turtles, fish) signal both ecological potential and risk. Seasonal flooding and unregulated human-animal interactions (e.g., feeding) pose ongoing threats.

Although NTPU employs automated water-level monitoring, it lacks real-time data on air and water quality, predictive analytics, and public access. To address this, we present a smart monitoring and forecasting system leveraging IoT infrastructure and deep learning. Using LoRaWAN [2], we enable low-power, campus-wide data collection. Forecasting models include GRU and LSTM networks, chosen for their ability to model temporal dependencies in time-series data, along with hybrid CNN-GRU and CNN-LSTM architectures. Transformer-based models further enhance long-range prediction through attention mechanisms. An ensemble approach balances accuracy and robustness, aligning with [3], which showed deep learning ensembles outperform traditional methods in environmental forecasting.

Our bilingual (Chinese-English) interface ensures accessibility, while the system enables proactive, data-driven responses. This research offers a scalable framework for sustainable campus practices and supports smarter environmental governance, echoing recommendations by [4].

II. RELATED WORK

Sustainable development within institutional environments is increasingly recognized as a key strategy for addressing global environmental challenges. University campuses, in particular, serve not only as operational units that can reduce their ecological footprint but also as living laboratories where students engage in hands-on learning. As emphasized by Alshuwaikhat and Abubakar [1], sustainable campus initiatives are essential for both environmental impact mitigation and the cultivation of environmental responsibility through experiential education.

To support such efforts, emerging technologies such as LoRaWAN have become central to modern environmental monitoring frameworks. Known for its long-range communication capability and low power consumption, LoRaWAN is especially suitable for outdoor and wide-area deployments, making it ideal for campus and remote environmental sensing. Its applications have been widely documented in smart city infrastructure, precision agriculture, and distributed sensor networks [2], [5], [9].

At the hardware level, cost-effective, Arduino-based sensor platforms have made real-time environmental monitoring more accessible and scalable. Recent developments include the use of compact and reliable sensor modules capable of measuring water quality parameters such as pH, dissolved oxygen, and total dissolved solids, as well as air pollutants like PM2.5. These sensor systems are lightweight, energy-efficient, and easy to deploy in both fixed and floating configurations, enabling detailed environmental assessments across complex ecosystems [6], [7], [8], [10].

In the domain of data analytics, deep learning has emerged as a superior alternative to traditional statistical methods for environmental prediction. Liu et al. [3] demonstrated that recurrent neural networks such as GRU and LSTM significantly outperform conventional models in predicting air quality metrics like PM2.5. These models are especially well-suited for time-series forecasting due to their ability to learn temporal dependencies and adapt to nonlinear patterns in environmental data. Furthermore, GRU and LSTM have been effectively utilized in predicting water temperature and other hydrological parameters with minimal preprocessing requirements, making them practical for real-time systems [11].

To enhance model performance further, hybrid architectures such as CNN-GRU and CNN-LSTM combine the spatial pattern recognition strengths of convolutional layers with the sequential learning capabilities of recurrent units. These hybrid models have shown improvements in both accuracy and generalization, particularly for multivariate environmental forecasting tasks. More recently, Transformer-based models have gained attention for their ability to model long-range dependencies using attention mechanisms. These models have demonstrated state-of-the-art results in complex time-series applications, including air quality and weather prediction scenarios [12].

Collectively, these technological advancements support the broader goals of the United Nations' 2030 Agenda for Sustainable Development [4], particularly in areas related to climate action, sustainable cities, and environmental data accessibility. The integration of IoT-based monitoring systems with advanced AI forecasting tools represents a scalable and forward-looking solution to promote environmental resilience, not only within campuses but across broader urban and ecological contexts.

III. METHODOLOGY

A. System Overview

The system is designed to provide real-time data collection, predictive analytics, and visualization to support the sustainability of the Mind Lake ecosystem at National Taipei University (NTPU). It employs IoT sensor nodes strategically placed around the lake to monitor key environmental parameters, including water temperature, pH, dissolved oxygen, and air quality. These sensors transmit data via a LoRaWAN network to a central gateway, which forwards the information to a cloud server for processing. The server hosts deep learning models that analyze trends and deliver real-time forecasts. Outputs are displayed through a bilingual (Chinese-English) web dashboard, making environmental insights accessible to students, researchers, and decision-makers. Designed with scalability and adaptability in mind, the system serves as both a monitoring and early-warning platform for flooding and pollution, and can be replicated in other campus or community environments.

B. Sensor Hardware and Node Deployment

The environmental monitoring system employs a variety of sensors, each carefully selected for its ability to measure crucial parameters that influence the ecosystem around Mind Lake. The sensors were integrated into Arduino Mega 2560 boards, which serve as the data acquisition units for the system. These sensors include:

- DS18B20 Water Temperature Sensor: A digital sensor used to measure water temperature at various points in the lake, crucial for understanding the thermal dynamics of the water body.
- Gravity Analog pH Sensor/Meter Kit V2: This sensor measures the pH levels of the lake's water, a key indicator of water quality and aquatic life health.
- Gravity Analog Dissolved Oxygen Sensor: This sensor tracks dissolved oxygen levels, which are essential for maintaining a healthy aquatic ecosystem.
- Grove TDS Sensor: This sensor measures the total dissolved solids (TDS) in the water, which serves as a proxy for water purity and pollution levels.
- SHARP GP2Y1023AU0F PM2.5 Sensor: This optical sensor is used to measure particulate matter (PM2.5) in the air, an important air quality parameter.

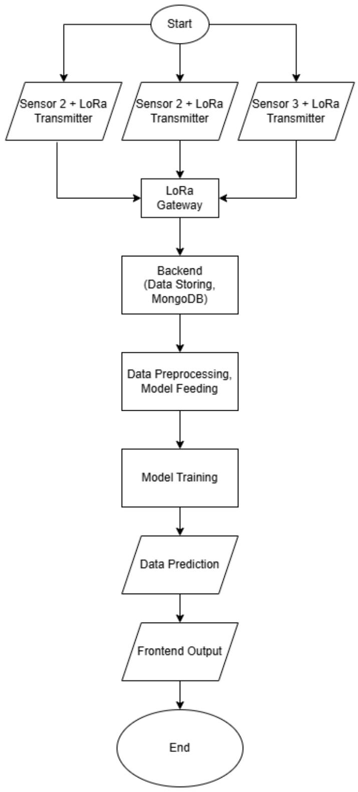

Fig. 1. Complete System Flowchart

Two sensor stations were deployed around Mind Lake:

- Floating Station: A custom-built floating platform made of large styrofoam supports the water quality sensors. This platform allows the sensors to move with the water, ensuring they provide accurate real-time data.
- PM2.5 Sensor Station: The PM2.5 sensor is mounted atop an electric box located near the lakeside. This station is dedicated to monitoring air quality near the lake and its surrounding area.

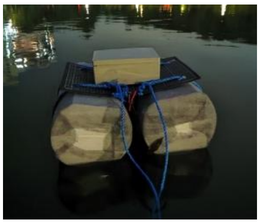

Fig. 2. Floating Station

Fig. 3. PM2.5 Sensor Station

These stations are strategically placed to ensure comprehensive coverage of both the lake's water and the surrounding air. The floating station is mobile and can adapt to changes in water level, while the PM2.5 sensor station provides continuous air quality data.

C. LoRaWAN Communication and Gateway Setup

The data from each sensor node is transmitted wirelessly using LoRaWAN (Long Range Wide Area Network), which is particularly well-suited for long-range communication in outdoor environments. The sensor nodes, each equipped with Heltec LoRa Wi-Fi ESP32 V3 kit, transmit data packets every 10 minutes. This protocol allows for low-power, long-distance communication, enabling the sensor nodes to operate independently for extended periods.

The data transmitted by the nodes is received by a Heltec HT-M7603 LoRaWAN Gateway, which acts as the intermediary between the sensor nodes and the cloud server. The gateway has a range of approximately 100 meters and is connected to The Things Network (TTN), a widely-used network that facilitates LoRaWAN communication. The data packets are then forwarded to a cloud-based server, where they are stored, processed, and analyzed.

This setup enables real-time environmental monitoring without requiring a wired infrastructure, making it an efficient and cost-effective solution for remote or large-scale deployment.

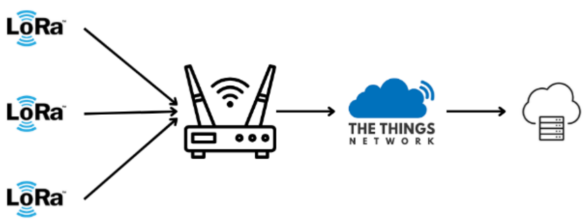

Fig. 4. LoRaWAN Topology

D. Backend System and Data Storage

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E. Data Preprocessing and Input Formatting

Before training deep learning models, the collected data undergoes several preprocessing steps. First, the raw sensor readings are cleaned to handle missing values through interpolation. The data is then normalized using MinMax scaling to bring all features within the same range, which helps improve the stability and performance of the deep learning models.

Each data sample represents a window of 48 consecutive data points (10-minute intervals), corresponding to a period of approximately 8 hours. The data is structured into sequences, with each sequence containing readings from all sensors. The sequences are used as inputs for the models, enabling the prediction of environmental conditions for the next 8 hours.

The dataset is split into 80% training and 20% testing sets. To further train the ensemble model, the training set is divided into 75% for base models and 25% for the ensemble model.

F. Model Architectures and Training

Five deep learning models are used to predict 8-hour environmental trends:

- GRU: Efficient for short-term patterns; two GRU layers followed by dense layers.
- LSTM: Captures long-term dependencies using stacked layers with sequence output.
- CNN+LSTM: Combines local feature extraction (CNN) with temporal learning (LSTM).
- CNN+GRU: Similar to CNN+LSTM but more lightweight due to GRU cells.
- Transformer: Utilizes attention mechanisms for long-range dependency modeling.

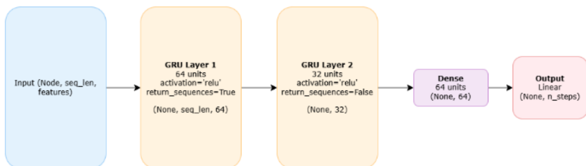

Fig. 5. GRU Architecture

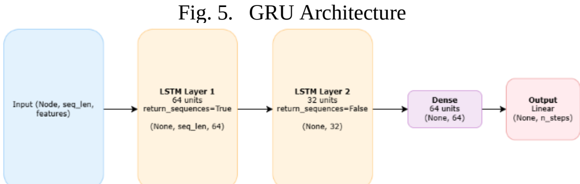

Fig. 6. LSTM Architecture

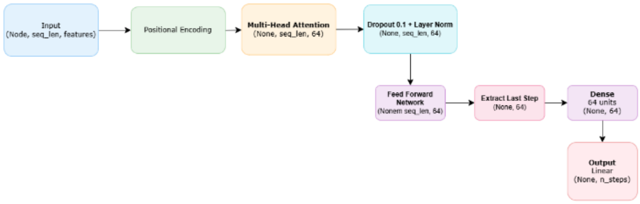

Fig. 7. CNN+LSTM Architecture

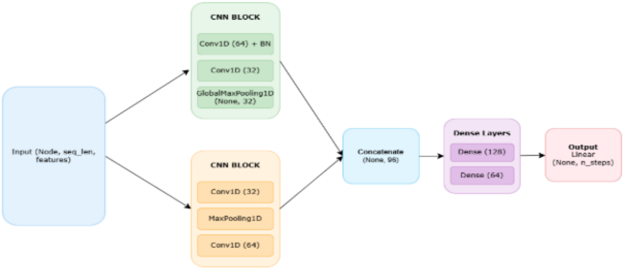

Fig. 8. CNN+GRU Architecture

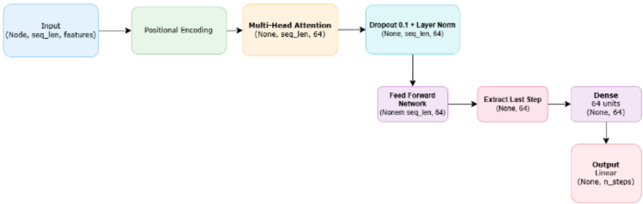

Fig. 9. Transformer Architecture

G. Ensemble Prediction Strategy

An ensemble learning approach was adopted to combine the outputs of the individual models and improve prediction accuracy. After training the base models, the ensemble model takes the predictions from each base model as input and generates a final forecast by combining the predictions in a weighted manner. This method helps to mitigate the individual weaknesses of the models and increase the robustness of the predictions.

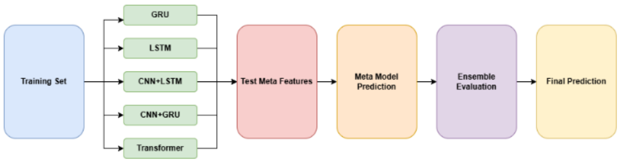

Fig. 10. Ensemble Architecture

IV. Results

A. Overview of Results

1) Data Source

Environmental data were collected from three IoT sensor nodes deployed around Mind Lake at National Taipei University between November 2024 and May 2025. Two nodes were installed on floating platforms within the lake, while one was mounted on an elevated electric box near the shoreline. Each device recorded measurements at 10-minute intervals.

The system monitored key environmental parameters, including water temperature, pH, electrical conductivity, dissolved oxygen, total dissolved solids (ppm), and PM2.5. Sensor readings were transmitted in real time via LoRaWAN, using the TTN (The Things Network) Console and MQTT protocol to forward data to a private MongoDB database hosted on the research lab's cloud server.

To address occasional packet loss during transmission, missing values were imputed using K-Nearest Neighbors (KNN) interpolation. The cleaned dataset was then normalized and used for time-series forecasting with various deep learning models.

2) Evaluation Metrics

Model performance was evaluated using RMSE, MAE, and R^2—metrics that assess prediction error magnitude, average deviation, and variance explained, respectively. The ensemble model, which combines outputs from all individual models, demonstrated superior forecasting accuracy overall, as detailed in the following analysis.

B. Model Performance Comparison

Tables below summarizes the evaluation metrics (R^2, MAE, and RMSE) for each of the individual models and the ensemble model, across the five environmental parameters measured. Each of these metrics provides insight into the models' ability to predict the environmental conditions accurately.

TABLE I. ONE-HOUR PREDICTION R^2 RESULT

R^2					
Model	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.9738	0.917	0.9397	0.899	0.9514
LSTM	0.9673	0.916	0.9387	0.889	0.942
CNN + GRU	0.9657	0.927	0.9453	0.904	0.9406
CNN + LSTM	0.9334	0.905	0.9079	0.903	0.9299
Transformer	0.9286	0.921	0.9334	0.874	0.9423
Ensemble	0.9797	0.942	0.9532	0.916	0.9515

TABLE II. ONE-HOUR PREDICTION MAE RESULTS

MAE					
Model	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.0108	0.076	0.0383	1.156	1.3813
LSTM	0.0123	0.078	0.0384	1.253	1.5111
CNN + GRU	0.0124	0.072	0.0377	1.243	1.7
CNN + LSTM	0.0173	0.08	0.0579	1.253	1.81
Transformer	0.0193	0.072	0.0467	1.661	1.76
Ensemble	0.0091	0.077	0.0341	1.179	1.37

TABLE III. ONE-HOUR PREDICTION RMSE RESULTS

RMSE					
Model	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.0196	0.101	0.0791	3.151	0.0103
LSTM	0.0214	0.105	0.078	3.124	0.0106
CNN + GRU	0.0228	0.099	0.0699	2.96	0.0113
CNN + LSTM	0.0265	0.112	0.0881	2.95	0.0111
Transformer	0.0265	0.091	0.0837	3.23	0.0105
Ensemble	0.0195	0.093	0.0656	2.843	0.0104

TABLE IV. FOUR-HOUR PREDICTION R^2 RESULT

R^2					
Model	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.9572	0.913	0.9075	0.798	0.9217
LSTM	0.9472	0.91	0.9094	0.804	0.9121
CNN + GRU	0.9347	0.914	0.9296	0.832	0.9145
CNN + LSTM	0.9097	0.892	0.883	0.837	0.9082
Transformer	0.9097	0.931	0.8942	0.796	0.9206
Ensemble	0.9554	0.948	0.9363	0.844	0.9244

TABLE V. FOUR-HOUR PREDICTION MAE RESULTS

Model	MAE				
	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.0139	0.08	0.0482	1.761	1.8329
LSTM	0.0154	0.082	0.0494	1.768	1.9837
CNN + GRU	0.0172	0.08	0.0437	1.659	2.01
CNN + LSTM	0.02	0.087	0.0648	1.659	2.12
Transformer	0.025	0.071	0.0524	1.807	1.93
Ensemble	0.0142	0.074	0.0408	1.603	1.87

TABLE VI. FOUR-HOUR PREDICTION RMSE RESULTS

Model	RMSE				
	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.0175	0.099	0.0768	3.202	2.8401
LSTM	0.0194	0.101	0.076	3.152	3.0105
CNN + GRU	0.0216	0.099	0.067	2.915	2.97
CNN + LSTM	0.0254	0.111	0.0864	2.82	3.08
Transformer	0.0254	0.088	0.0821	3.156	2.86
Ensemble	0.0178	0.091	0.0637	2.807	2.79

TABLE VII. EIGHT-HOUR PREDICTION R^2 RESULT

Model	R^2				
	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.9153	0.894	0.8686	0.726	0.8718
LSTM	0.8986	0.878	0.8735	0.729	0.8646
CNN + GRU	0.8652	0.891	0.8951	0.75	0.8728
CNN + LSTM	0.8843	0.87	0.8735	0.732	0.8697
Transformer	0.8843	0.927	0.8549	0.706	0.8771
Ensemble	0.9046	0.946	0.9091	0.763	0.8795

TABLE VIII. EIGHT-HOUR PREDICTION MAE RESULTS

Model	MAE				
	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.0203	0.088	0.0604	2.208	2.2243
LSTM	0.022	0.095	0.0604	2.198	2.3629
CNN + GRU	0.0255	0.09	0.0533	2.084	2.24
CNN + LSTM	0.0227	0.097	0.0723	2.198	2.38
Transformer	0.0306	0.073	0.0633	2.269	2.22
Ensemble	0.021	0.075	0.0502	2.045	2.1

TABLE IX. EIGHT-HOUR PREDICTION RMSE RESULTS

Model	RMSE				
	Water Temperature	pH	Oxygen	PM2.5	TDS/EC
GRU	0.0246	0.111	0.0914	3.658	3.603
LSTM	0.027	0.1194	0.0897	3.635	3.7032
CNN + GRU	0.0311	0.1128	0.0817	3.492	3.59
CNN + LSTM	0.0288	0.123	0.0955	3.55	3.63
Transformer	0.0288	0.092	0.0955	3.722	3.53
Ensemble	0.0261	0.0937	0.0761	3.4	3.49

C. Performance Analysis of Individual Models

The evaluation of all models using R², MAE, and RMSE across 1-hour, 4-hour, and 8-hour predictions reveals distinct strengths and limitations for each approach. Among the individual models, GRU consistently performed well in predicting water temperature and total dissolved solids (TDS), showing strong accuracy and low error across all time horizons. Its ability to capture stable and consistent patterns made it particularly effective for these parameters. However, GRU was less accurate when handling more dynamic variables like PM2.5 and pH.

LSTM demonstrated solid overall performance, especially in predicting dissolved oxygen and pH levels. Its strength in modeling long-term dependencies contributed to its effectiveness in these areas. That said, it lagged behind GRU in forecasting TDS and showed slightly weaker accuracy for PM2.5.

The CNN+GRU hybrid model excelled in PM2.5 forecasting, benefiting from the CNN's local feature extraction combined with GRU's sequence modeling. Despite this strength, its performance in water temperature and pH prediction was less impressive, with other models such as GRU and Transformer performing better in those categories.

Similarly, CNN+LSTM provided reasonable results across all metrics, especially for pH and PM2.5. However, it did not lead in any specific parameter and generally showed balanced, yet unremarkable performance compared to more specialized models.

The Transformer model stood out in pH prediction, achieving the highest accuracy in this category, thanks to its attention mechanism and ability to handle long-range dependencies. However, its effectiveness dropped when forecasting PM2.5 and TDS, where models like CNN+GRU and GRU delivered better results.

Among all, the ensemble model consistently delivered the most stable and accurate results. By combining the strengths of each individual architecture, it achieved the best performance in oxygen, PM2.5, and TDS predictions, and maintained top results across nearly all other parameters. This highlights the robustness and generalizability of ensemble learning for environmental forecasting applications.

V. ANALYSIS

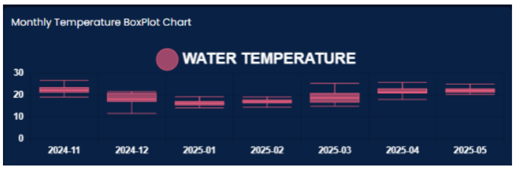

Fig. 11. Water Temperature BoxPlot Chart

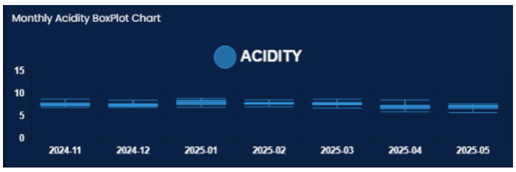

Fig. 12. Acidity(pH) BoxPlot Chart

Fig. 13. Conductivity (EC) BoxPlot Chart

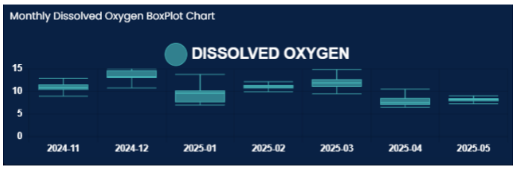

Fig. 14. Dissolved Oxygen BoxPlot Chart

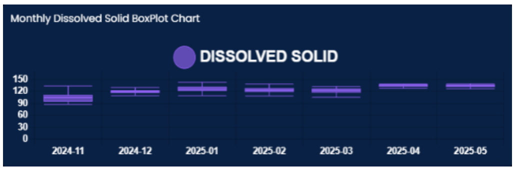

Fig. 15. Dissolved Solid(ppm) BoxPlot Chart

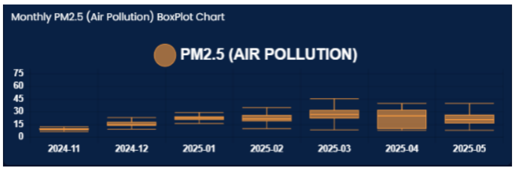

Fig. 16. PM2.5 BoxPlot Chart

Monthly box plots, supported by field observations, reveal key seasonal and ecological patterns around Mind Lake. Water temperature follows expected seasonal trends, with cooler medians from November to January and warmer values from March to May, reflecting a natural thermal cycle that impacts oxygen levels and aquatic activity.

pH levels remain within a stable alkaline range (7–9), with minor monthly variation. Notably, once a shift occurs, the pH tends to stabilize in that range for 1–2 months, suggesting a buffered system or prolonged external influence such as runoff or biological processes.

Dissolved oxygen (DO) mostly ranges from 6–12 mg/L, with greater variability observed between November and January. From February onward, levels stabilize, indicating balanced aerobic conditions. While conductivity remains low, its consistency should be considered alongside the rising TDS trend.

TDS displays a clear upward trend from late 2024 to 2025, aligning with visual signs of algae growth and greenish water—likely indicating increasing organic matter and early-stage eutrophication.

PM2.5 shows the greatest variability, especially from February 2025 onward, with values spiking above 40 µg/m³. Field data suggests a sharp drop in PM2.5 after rainfall, especially when levels exceed 25 µg/m³, reflecting a strong negative correlation between rainfall and air pollution. This effect is most pronounced from March to May.

VI. DISCUSSION

A. Real-Time Prediction Capabilitites

One of the key features of the system is its ability to provide real-time predictions, with each prediction step taking only 10ms to compute. This quick response time is crucial for applications like flood forecasting and air quality monitoring, where timely decisions can prevent potential disasters. The system's ability to predict parameters such as water temperature and PM2.5 almost instantaneously makes it suitable for deployment in environments where real-time intervention is required.

While the ensemble model provided the most stable and accurate predictions, it is important to note that individual models also offer valuable insights for specific parameters. For example, GRU performed best for water temperature and TDS, while Transformer excelled in pH predictions. This highlights the importance of selecting the right model based on the parameter being predicted.

B. Model Comparisons and Improvements

The comparison between individual models and the ensemble model highlights that combining models can lead to a more robust system, especially when different models capture different aspects of the data. The moderate improvements in performance metrics for the ensemble model suggest that there is still room for refinement. For instance:

- Fine-tuning individual models: Models like CNN+LSTM and Transformer showed promise for specific parameters (PM2.5 and pH), and further fine-tuning these models could enhance their overall performance.
- Ensemble weighting: The ensemble model could be further optimized by adjusting the weights of the individual models based on their performance for specific parameters. For example, GRU might be given more weight for predicting water temperature and TDS, while Transformer could be emphasized for pH prediction.

C. Limitations and Challenges

While the system shows strong overall performance, several limitations and challenges must be addressed:

- Sensor Accuracy: The accuracy of predictions depends heavily on the quality of the sensor data. Any inconsistencies or errors in the sensor measurements, such as noise or calibration issues, can affect model predictions. Future work could explore sensor calibration techniques or the use of additional sensor types to improve data reliability.
- Generalization: While the system performed well on the NTPU Mind Lake dataset, further testing on other environments (e.g., different campuses or urban areas) is necessary to validate the generalizability of the models. Environmental conditions can vary widely across locations, which may affect model accuracy.
- Data Availability: The success of the system relies on continuous data collection over long periods. For real-time prediction, a steady stream of accurate data is essential. Data gaps or interruptions in sensor readings could undermine prediction accuracy, especially in real-time scenarios.
- Computational Efficiency: The ensemble model provided better results but requires more computational resources due to the need to run multiple models in parallel. Future improvements could focus on model pruning or exploring more efficient ensemble techniques to reduce computational costs.

D. Future Work and Directions

Several avenues for future work can improve the system:

Model Enhancement: As noted, fine-tuning the individual models, especially for PM2.5 and pH, could lead to better performance. Incorporating hybrid models or exploring other deep learning techniques, such as attention mechanisms for PM2.5 prediction, could further improve results.

Integration with Other Environmental Data: Future iterations of the system could integrate additional environmental variables, such as weather data (temperature, humidity) or real-time weather forecasts, to provide more comprehensive and accurate predictions. This could further improve the robustness of the system in forecasting complex environmental phenomena.

Scalability: Expanding the system to cover larger areas and more stations could provide valuable insights for broader applications, such as urban monitoring and sustainable city planning. The system's modular design makes it easy to scale and deploy in other locations with minimal additional setup.

User Feedback: Incorporating real-time user feedback from environmental managers and other stakeholders could help refine the system. Feedback on prediction accuracy and actionable insights would be invaluable for adapting the system to real-world needs.

Conclusion

The proposed environmental monitoring system successfully demonstrates the application of deep learning models and IoT technology to provide real-time predictions of critical environmental parameters. While the ensemble model offers the best overall performance, each individual model shows specific strengths for different parameters. This makes the system adaptable to various environmental monitoring applications. Future improvements, including model fine-tuning, data integration, and scalability, will enhance its effectiveness and enable broader deployment.

VII. Conclusion

The proposed environmental monitoring system successfully demonstrates the application of deep learning models and IoT technology to provide real-time predictions of critical environmental parameters. While the ensemble model offers the best overall performance, each individual model shows specific strengths for different parameters. This makes the system adaptable to various environmental monitoring applications. Future improvements, including model fine-tuning, data integration, and scalability, will enhance its effectiveness and enable broader deployment.

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