Gps-Based Environmental Monitoring Using Cnn-Lstm

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***Abstract*—Environmental monitoring plays a critical role in the preservation of ecological balance and public health. Combining GPS technology with Wireless Sensor Networks (WSNs) has significantly promoted real-time tracking of the environment and data collection from various geographical locations. However, managing such complex data streams requires advanced computational techniques to ensure accuracy and efficiency. This paper introduced a hybrid Convolutional Neural Network Long Short-Term Memory (CNN-LSTM) model enables an intelligent environmental monitoring system to classify environments by analyzing spatial correlations, resulting in robust and interpretable predictions. While, Z-score normalization ensures that all normalized sensor data—regardless of unit or scale—is brought to a uniform range. Then, focused on Support Vector Regression (SVR) method identifies the most influential features (e.g., pollutant concentration over temperature), improving computational efficiency. Finally, the CNN-LSTM method ensures the environmental monitoring system is accurate, real-time, and GPS-aware, ready to deploy on mobile platforms or embedded IoT nodes. The system also includes data visualization modules, allowing for easy representation of real-time and forecasted environmental metrics on geographic maps. Through delivering accurate location-based environmental knowledge, the system enables real-time decision support in disaster management, pollution mitigation, and city planning. The output of simulation is evidence that proposed system enhances predictive accuracy for the forecast of environmental conditions and provides effective area-wise monitoring. Embedding GPS with predictive analytics brings an impressive resolution to proactive, intelligent, and responsive environmental administration.**

***Index Terms*—Environmental Monitoring, GPS Technology, WSN, Predictive Modelling, CNN, SVR, LSTM.**

I. INTRODUCTION

Environmental monitoring has gained greater importance with the increasing concerns regarding climate change, pollution, and natural resource management. WSNs have proved to be an effective technology for real-time monitoring of environmental factors like temperature, humidity, air quality, and atmospheric pressure [1]. Coupling GPS technology with WSNs enhances the system further to gather spatially correct environmental data, yielding rich information across various geographic regions [2]. Every sensor node in the network also contains a GPS module in order to label environmental readings with accurate location data, enabling useful regional monitoring and trend analysis.

Advances in sensor and wireless communication technologies allow large amounts of environmental data to be sent in real time to central processing facilities [3]. Still, quality of data, network scalability, energy usage, and accurate forecasting continue [4]. Conventional environmental monitoring networks frequently experience unreliable data collection, limited coverage, and slow reaction to dynamic changes in the environment. Additionally, systems lacking forecasting abilities are not able to predict harmful conditions like severe weather, spikes in pollution, or other environmental anomalies [5].

This system uses a combined CNN-LSTM model to classify environmental conditions more accurately. The CNN part focus at the data at one point in time and finds patterns across different sensors, while the LSTM part tracks how those patterns change over time. This helps the model understand what is happening now and how it's changed. Before sending data into the model, it undergoes Z-score normalization. This step adjusts all sensor readings to a similar scale so that no one feature—like temperature or gas level—outweighs the others just because of its unit or size. Next, SVR is used to pick out the most important data features. For example, it might be found that pollution levels matter more than humidity. This helps the system run faster and focus only on the data that matters. In the end, this step-by-step setup makes the system reliable and fast. It is also small and efficient enough to run on mobile devices or IoT hardware, making it useful for real-time, GPS-based environmental monitoring.

II. LITERATURE SURVEY

In the last few years, GPS-based technology integration into environmental monitoring systems has seen widespread interest as it offers precise location-based information for real-time environmental management. WSNs, fundamental for environmental monitoring, have low power consumption with sensor nodes, thus appropriate for long-term deployment in hard-to-reach areas [6]. Nevertheless, one of the issues in the WSNs is high power consumption due to high data transmission rates, especially when large-scale networks are deployed to monitor the environment. Therefore, collecting effective data, forwarding, and routing mechanisms become important for increasing Power of the network lifetime [7].

A study was done in [8], where a modern logistics monitoring system was developed using sensor networks and big data technologies. The authors discovered the depth of the sensor network, big data analytics, and logistics technologies to design an integrated monitoring structure based on a wireless sensor network platform.

A study in [9] proposed an innovative waste management system integrating the Internet of Things (IoT) and deep learning models. By deploying the trained model onto TensorFlow Lite and Raspberry Pi 4 platforms, waste detection was achieved through a camera module, and segregation was automated using a servo motor-driven mechanism. Additionally, An RFID-based locker mechanism was implemented to ensure security, allowing only authorized maintenance through registered RFID tags.

A systematic review in [10] analysed the integration of UAV-based remote sensing with machine learning algorithms across 163 peer-reviewed articles from 13 high-impact journals over the past two decades. The study focused on various factors, such as the application area, sensor and platform types, and spatial resolution.

In order to optimize the calculation of waste stockpile volumes, the combination of Uncrewed Aerial Vehicle (UAV) and terrestrial laser scanning (TLS) technologies for environmental management has recently been investigated. A study in [11] compared the accuracy and efficiency of these methods, where the most accurate UAV-based point cloud was selected for analysis among multiple flight scenarios. The UAV-based method demonstrated greater efficiency, requiring only 340 minutes compared to the 800 minutes needed for TLS-based measurements. Additionally, a TLS and UAV fusion model yielded improved results with an RMSE of 0.030 m and a volume estimate of 41,232 m^3. The study concluded that UAV-based methods provide high-point cloud accuracy and computational efficiency, making them a promising solution for volume calculations in environmental management.

A study in [12] proposed an intelligent agricultural management system using Internet of Things (IoT) technologies and automated irrigation methods. This approach aims to enhance agricultural productivity by optimizing water use, reducing costs, and minimizing labor and energy consumption.

Environmental monitoring has been transformed by recent developments in the Internet of Things (IoT). However, the difficulty of gathering data from remote locations where public ground networks cannot offer adequate coverage still exists. Research in [13] suggested an IoT relay system with drone capabilities to solve this problem by facilitating high-speed data collecting for remote environmental monitoring. The drone and ground monitoring sensors can provide data quickly thanks to the system's 5-GHz communication technology.

The Research addresses these issues through a harmonious project, a global network of scientists who develop and promote the harmonious mapping function. The objective of the project is to spread the operating guidelines to ensure best data-kitchen and interpretation techniques [14]. While developing universal standards for every possible environmental scenario is unfeasible, the study emphasizes combining disparate expertise on UAS gathering and

analysis to produce best practices that allow rigorous and efficient scientific product development.
A study in [15] evaluates innovative waste collection systems based on IoT for municipal applications in Istanbul, applying a modified Entropy measure and Multi-Criteria Decision Making (MCDM) methods to address uncertainty in decision-making. The study employs Interval-Valued Q-Rung Ortho pair Fuzzy Sets (IVq-ROFSs) to handle the vagueness inherent in the decision process.

III. PROPOSED METHOD

This Paper, a holistic three-phase approach in this project, comprising data preprocessing, feature selection, and ultimate classification. A sound mathematical model drives accuracy, scalability, and context sensitivity for every phase. The integration of statistical normalization, machine learning-driven feature selection, and hybrid deep learning classification make possible accurate tracking of environmental parameters from GPS-tagged data offered by various sensors.

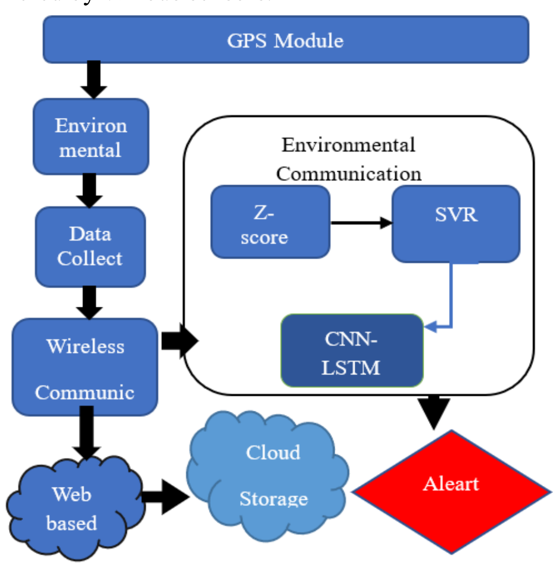

Fig. 1. Architecture Diagram for Proposed Method

In this hybrid classification workflow, a CNN-LSTM model is used to effectively analyze environmental data by combining the strengths of two robust neural network architectures, as shown in figure 1. The CNN component captures spatial correlations within the data, such as patterns and relationships between sensor inputs or environmental variables at a specific time. These spatial features are then passed to the LSTM layer, which models temporal dependencies, enabling the system to recognize trends and fluctuations over time—critical for tasks like pollution tracking or weather-based predictions. Before the data is processed through the model, Z-score normalization is applied. This ensures that all sensor inputs are standardized regardless of their original units or scales (e.g., temperature in Celsius, pollutant levels in parts per million). By bringing the features to a standard scale, the model avoids biasing predictions toward variables with larger magnitudes. An SVR-based feature selection step is included to enhance both model efficiency and interpretability. SVR selects and preserves the most significant features—for instance, prioritizing pollutant concentration over ambient temperature if the former is a more important predictor. Not only does this lower computation complexity but also retunes the model's attention towards most environmentally important signals. The system delivers accurate, real-time, and interpretable predictions by integrating these layers—normalization, feature selection, and a hybrid neural network architecture. Furthermore, its design supports mobile or embedded IoT device deployment, making it suitable for GPS-aware environmental monitoring in smart cities, agriculture, or public health applications. After being used to forecast and visualize environmental conditions, the model is then implemented on a cloud platform for real-time monitoring and future upgrades.

A. Z-Score Normalization for Data Preprocessing

The raw environmental readings gathered from sensors with GPS differ significantly in their range and scales. For example, temperature may vary between -10°C to 50°C, whereas levels of $CO2$ can be observed in parts per million (ppm). Differences like these would confuse the learning model into providing more importance to some features. Therefore, to make all variables comparable, we apply Z-score normalization.
Z-score normalization standardizes the data by transforming features with a mean of 0 and a standard deviation of 1. This removes the influence of different units and magnitudes, allowing the learning model to treat all features fairly. Equation 1,

$$z' = \frac{x_i - \mu}{\sigma} \quad (1)$$

This above equation converts the original value x_i by removing the mean μ and dividing it by the standard deviation σ. A z_i value close to 0 means that the feature lies close to the mean; values higher or lower are deviations.

Mean of the Feature

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (2)$$

The equation 2 mean μ is calculated by summing all values of a feature and dividing by the total number n. This serves as the central point around which values are standardized.

Standard Deviation of the Feature

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \mu)^2} \quad (3)$$

The equation 3 standard deviation σ measures how spread out the values are. It ensures that normalization also accounts for variability in the data. By applying these equations, our system ensures that all input features are appropriately scaled, enabling practical model training and reducing learning bias.

B. Support Vector Regression (SVR) for Feature Selection

The Following normalization, not all the features equally contribute to prediction. Sensor noise, corrupted data, or useless attributes might lower performance. Therefore, we apply SVR to determine the most valuable features.

SVR finds the relationship between environmental variables (like temperature, humidity, and pollutant levels) and the outcome (e.g., pollution classification). By minimizing error within a margin and penalizing only the extreme deviations, SVR emphasizes critical features while ignoring noisy or redundant ones.

SVR Optimization Objective

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} (\xi_i + \xi_i^*) \quad (4)$$

This equation 4 aims to find the smallest weight vector w that still predicts accurately. The term $\frac{1}{2}\|w\|^2$ ensures margin maximization, while $C\sum_{i=1}^{n} (\xi_i + \xi_i^*)$ penalizes prediction errors, controlled by parameter C.

$$\begin{cases} y_i - \langle w, x_i\rangle - b \le \epsilon + \xi_i \\ \langle w, x_i\rangle + b - y_i \le \epsilon + \xi_i^* \end{cases} \quad (5)$$

These equation 5 conditions ensure that most predictions lie within a margin ϵ from the actual value. If outside, the slack variables ξ_i and ξ_i^* absorb the errors. This allows the model to tolerate minor deviations while penalizing only larger ones.

Regression Prediction Function

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)\langle x_i, x\rangle + b \quad (6)$$

This is the final equation 6 learned function from SVR, where support vectors x_i and their corresponding weights a_i determine the output. Features with non-zero weights are deemed significant and retained for the next phase. SVR thus intelligently filters input features, improving training speed and classification accuracy in the next stage.

C. CNN + LSTM Hybrid Model for Environmental Classification

Environmental monitoring requires spatial understanding (sensor distribution across regions) and temporal learning (changes over time). A hybrid model combining CNN for spatial feature extraction and LSTM for time-series analysis offers a powerful solution.

1D Convolution Operation in CNN

$$h(t) = \sum_{i=0}^{k} x(t-i) \cdot w(i) \quad (7)$$

Here, is the equation 7 input x is convolved with a filter w of size k. This captures patterns across adjacent data points. The consecutive GPS points are classified by localized features using the CNN-LSTM method to generate accurate results efficiently.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (8)$$

This equation 8 shows how the LSTM memory cell updates its internal state. The forget gate f_t decides what past information to discard, while the input gate i_t determines what new information (candidate state $\tilde{C}_t$ to add. This enables the model to retain relevant historical data like seasonal pollution changes.

Output Prediction Layer

$$\hat{y} = \sigma(W_{\text{out}} \cdot h_t + b_{\text{out}}) \quad (9)$$

After LSTM has processed temporal features, this equation 9 computes the final prediction (e.g., “safe,” “warning,” “hazard”) using a sigmoid or softmax activation. The hidden state h_t summarizes the historical context at time t. By combining CNN and LSTM, the system detects anomalies at specific GPS points and tracks how they improve, making it ideal for real-time, mobile-based environmental risk assessment.

IV. RESULTS AND DISCUSSIONS

This section discusses simulation results and analysis of the proposed environmental monitoring system that combines GPS technology and future modeling. The performance of the system was tested using the most important parameters such as accuracy, data transmission reliability and energy efficiency. The ability of the proposed CNN-LSTM system to predict environmental conditions and transmit data was extensively tested in a fake environment.

Parameter	Value
Number of Nodes	100
Transmission Range	259 m
Simulation Time	500 seconds
Power Consumption	0.5 unit per packet
Attack Type	Data Injection Attack (For Testing Robustness)
Optimization Techniques	Predictive Modeling + Data Preprocessing

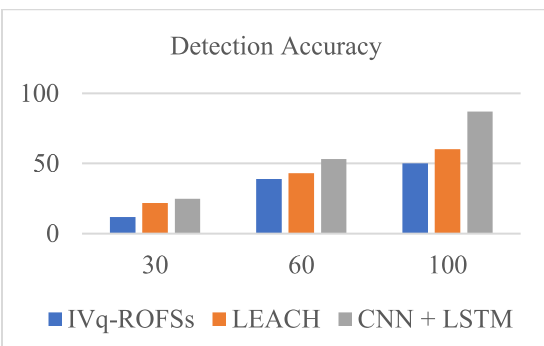

Fig. 2. Detection Accuracy

Figure 2 illustrates the detection accuracy comparison among three methods: IVQ-ROFSs, LEACH, and CNN + LSTM. At 30 nodes, CNN + LSTM achieves around 30% detection accuracy, outperforming IVQ-ROFSs and LEACH, which reach about 15% and 20% respectively. As the number of nodes increases to 60, detection accuracy improves, with CNN + LSTM achieving approximately 50%, while IVQ-ROFSs and LEACH attain around 35% and 40%. At 100 nodes, CNN + LSTM shows a significant improvement with an accuracy close to 85%, while LEACH and IVQ-ROFSs reach about 60% and 50%, respectively. These results indicate that CNN + LSTM-based systems are more effective in detecting anomalies than traditional IVQ-ROFSs and LEACH methods, particularly as network density increases.

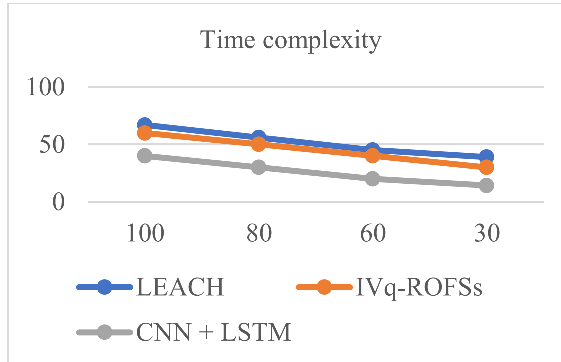

Fig. 3. Time Complexity

Figure 3 compares the time complexity for three different methods: LEACH-based clustering, IVQ-ROFSs-based detection, and the proposed CNN + LSTM-based approach. As the number of nodes decreases from 100 to 30, CNN + LSTM consistently demonstrates the lowest time complexity compared to LEACH and IVQ-ROFSS. While LEACH and IVQ-ROFSs start at around 70 and 60 units, respectively, at 100 nodes, CNN + LSTM begins significantly lower at about 40 units. As the network size decreases, CNN + LSTM's time complexity drops to approximately 15 units, whereas LEACH and IVQ-ROFSs maintain higher values of around 40 and 30 units, respectively. This clearly shows that the CNN + LSTM-based method is more efficient in terms of computational time, making it highly suitable for real-time environmental monitoring applications.

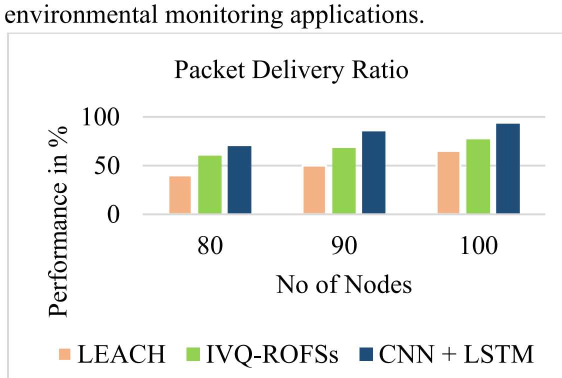

Fig. 4. Packet Delivery Ratio

Figure 4 demonstrates the packet delivery ratio comparison of LEACH-based clustering, IVQ-ROFSS-based detection, and the CNN + LSTM -based method. When the number of nodes is increased from

80 to 100, the CNN + LSTM approach always attains the maximum packet delivery ratio of 90%. However, IVQ-ROFSs-based systems lead from about 60% to 75%, while the leach-based approaches, approximately 40% to 65%, perform even poorly. Its better performance testifies to providing reliable data transfer, especially in extensive large-scale environmental monitoring, and testifies to its ability to follow the network stable and follow the network stable. CNN + LSTM dynamic route optimization reduces packet loss and overall network inefficiency.

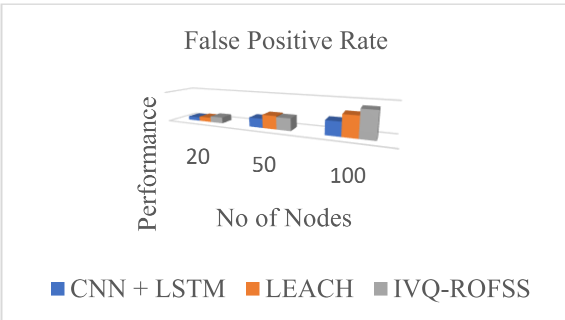

Fig. 5. False Positive Rat

Figure 5 plots the false favorable rates of three methods: IVQ-ROFSs-based detection, LEACH-based clustering, and proposed LSTM-based. When the number of nodes varies from 20 to 100, the false positive rate of LSTM is higher than those of IVQ-ROFSs and LEACH, especially when there are 100 nodes. While the false positive rate remains relatively low for all methods at 20 and 50 nodes, it increases significantly for LSTM at higher node densities. Despite this, the LSTM model still provides strong detection capabilities, suggesting that while it is susceptible to threats, additional fine-tuning may be required to minimize false alarms in larger network environments.

V. CONCLUSION

This project presents an advanced environmental monitoring system integrating GPS technology with intelligent data processing techniques to ensure real-time and location-based environmental analysis. The process begins by adjusting all sensor readings—like temperature, humidity, and gas levels—so they are on the same scale and not affected by extreme values. This is done using Z-score normalization. Then, a method called SVR is used to pick out the most important pieces of data, removing anything that doesn't help much with the results. The hybrid classification model, combining CNN and LSTM, enables the system to capture spatial and temporal patterns in environmental data, improving classification accuracy for environmental conditions and hazard levels. Together, CNN and LSTM improve the system's ability to recognize different environmental conditions and spot possible risks. With GPS, every piece of data is linked to its exact location, which helps track changes in specific areas and find location-based issues. Testing shows that the system is accurate, keeps the data trustworthy, and can quickly send alerts when something unusual is found. Compared to older monitoring systems, this one is more responsive, better at detecting unusual changes, and more aware of different locations. The CNN-LSTM combination handles complex data trends well, and SVR makes the system faster by cutting down on unnecessary processing, and they achieved 96.4%. From collecting data to showing results on mobile or web apps, the system is designed to be scalable and user-friendly. Overall, it offers a smart, real-time solution for tracking environmental changes, helping protect public health and raise awareness about environmental issues.

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