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IoT-Enabled Real-Time Environmental Monitoring and Disaster Prediction System

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Abstract
Environmental disasters floods, wildfires, landslides, earthquakes, and extreme air quality events collectively claim over 70,000 lives and inflict $200 billion in economic damage annually. Timely, accurate warning systems can dramatically reduce these tolls; yet most existing approaches rely on sparse, manually operated sensor networks with limited predictive capability. This paper presents a comprehensive IoT-enabled real-time environmental monitoring and disaster prediction system that integrates a heterogeneous wireless sensor network (WSN), a three-tier edge-cloud processing architecture, and a deep learning-based predictive engine. Eight categories of environmental sensors stream data through MQTT and LoRaWAN protocols to edge computing nodes (Raspberry Pi 4 and NVIDIA Jetson Nano) for preprocessing, anomaly detection, and local inference, with refined data forwarded to a cloud platform running Apache Kafka, InfluxDB, and a trained LSTM prediction model. Evaluated across six disaster categories on a six-month real-world deployment in the Western Ghats region of Maharashtra, India, the proposed system achieves 96.4% prediction accuracy with a mean lead time of 72 minutes before disaster onset. MQTT end-to-end latency is 12 ms on average, while energy consumption from the cloud is reduced by 34% using edge-offloading technique compared to the cloud-based approach alone. This study shows that scalable and low-latency IoT frameworks together with temporal deep learning make an effective early warning platform for smart cities and disaster zones.

Keywords: Wireless Sensor Networks, Internet of Things, LSTM, MQTT, Environmental Monitoring, Edge Computing, Smart Cities, LoRaWAN, Apache Kafka, Disaster Prediction.

1. INTRODUCTION

Natural calamities have been on the rise over the last two decades due to factors like climate change, fast urbanization, and increased human habitation in sensitive ecological areas. As per UNDRR, there were 7,348 disasters between 2000 and 2019, which is almost double the number of cases registered during the previous two decades. In the South Asian subcontinent, India alone witnesses over 900 occurrences of natural disasters within a decade, including monsoon floods, landslides in Himalayan and Western Ghats mountain ranges, and forest fires in the peninsula areas.

Three major deficiencies exist within the traditional environmental monitoring system comprised of government-owned weather stations, manual measurements of water level gauges along rivers, and satellite-based imagery: These deficiencies include the following:

1) Spatial sparseness (gaps in coverage of tens to hundreds of kilometers),
2) Latency in information delivery (information available once per hour or day), and
3) Being reactive instead of proactive.

Internet of Things (IoT) represents a paradigm that provides a groundbreaking solution. Tiny, cheap sensors transmitting data through wireless networks with minimal power consumption enable deployment at a scale never before achieved, resulting in fine-resolution monitoring of one's environment on the neighborhood or even home level. Combined with edge computing hardware and advanced machine learning algorithms that detect multivariate preconditions, these networks turn into real-time warning systems.

This paper makes the following key contributions to the literature:

- Design and deployment of an eight-sensor heterogeneous IoT node capable of monitoring temperature, humidity, air quality, seismic activity, rainfall, water level, wind speed, and soil moisture simultaneously at sub-second sampling rates.
- Three-layered processing framework involving sensors, edge, and cloud to ensure optimal combination of timely local inference and global training, ensuring overall round-trip latency below the 30ms threshold of real time for most sensor data streams.
- A multi-variable time-series prediction system based on LSTM using six months of field data collected by 48 sensors in the Western Ghats region, providing an accuracy rate of 96.4% and an AUC-ROC value of 0.978 for six types of disasters.
- A comparative evaluation of six communication protocols (MQTT, CoAP, HTTP/REST, WebSocket, LoRaWAN, and WebRTC) for IoT-to-edge data transport, with quantified latency and energy profiles.
- Integration with a multi-channel alert dissemination pipeline (SMS, push notification, GIS dashboard) capable of reaching target communities within 90 seconds of a confirmed prediction.

The rest of the paper is organized as follows. Section 2 discusses relevant literature. Section 3 discusses the architecture of the system. Section 4 discusses sensor and network technology. Section 5 discusses the approach to machine learning. Section 6 discusses the experiment results. Section 7 discusses results and limitations. Section 8 concludes the paper.

2. RELATED WORK

2.1 IoT-Based Environmental Monitoring

Initial IoT-based environmental monitoring systems consisted of one-variable networks. The idea behind IoT in the area of environmental monitoring is provided by Gubbi et al. (2013), however, predictive analysis was not discussed. A temperature-humidity sensor-based system consisting of 32 nodes was developed by Kumar and Patel (2018). Although the system was capable of creating urban heat island maps with a high density, it had no functionality concerning predictions or alerts. LPWAN technologies for environmental IoTs have been studied by Raza et al. (2017) who concluded that LoRaWAN was the most efficient solution in rural areas.

More recent systems have incorporated multiple parameters. Arshad et al. (2020) built a five-sensor water-quality monitoring buoy with cloud-based anomaly detection, achieving 89% accuracy on pollutant events with 22-minute lead times. Chen et al. (2021) deployed a 120-node wildfire monitoring network in California using solar-powered LoRa nodes, detecting fire precursors (rising temperature + falling humidity + wind shift) with 85.6% accuracy. Neither system, however, integrated seismic or soil-moisture channels, which are essential for landslide prediction.

2.2 Disaster Prediction Machine Learning

Machine learning approaches to environmental disaster prediction span classical statistical models through modern deep learning. Recurrent Neural Networks (RNNs) and their variants Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have proven particularly effective for multi-variate environmental time-series prediction due to their capacity to model long-range temporal dependencies. Kratzert et al. (2019) demonstrated that LSTM-based rainfall-runoff models outperformed the Sacramento Soil Moisture Accounting model in 241 out of 241 catchments in the MOPEX dataset. Zhang et al. (2020) applied Bi-LSTM to earthquake aftershock sequence prediction, achieving 74% accuracy at 15-minute lead time notably

lower than the 94.2% this work achieves for flash flood prediction, reflecting the fundamental unpredictability of seismic sequences.
Transformer-based architectures have recently emerged as strong competitors. Wu et al. (2021) proposed a Temporal Fusion Transformer (TFT) for flood forecasting that outperforms LSTM by 3–5% on RMSE metrics; however, TFT requires substantially larger training datasets and is computationally prohibitive for on-device edge inference, which motivates our choice of LSTM as the backbone.

2.3 Edge Computing for IoT

The rationale for edge computing in IoT disaster systems is compelling: cloud round-trip times of 50–200 ms are too slow for sub-second seismic or flood-onset detection. Shi et al. (2016) coined the term "edge computing" and demonstrated 10x latency reduction for IoT workloads by processing at network edge nodes. Bonomi et al. (2012) introduced fog computing as an extension of cloud services to the edge, specifically for latency-sensitive IoT applications. In the disaster context, Mehmood et al. (2020) evaluated NVIDIA Jetson Nano for on-device inference in a wildfire detection UAV, achieving 91% accuracy at 28 fps validating edge AI inference hardware for real-time sensor processing.
A critical gap in existing work is the absence of end-to-end integrated systems that combine: (i) high-density multi-parameter sensing, (ii) edge preprocessing and local prediction, (iii) cloud-based global model training, and (iv) automated multi-channel disaster alerting. The present work addresses this gap with a deployed, field-validated system.

3. PROPOSED SYSTEM ARCHITECTURE

3.1 Architecture Overview

The proposed system adopts a three-tier hierarchical architecture illustrated in Figure 1. The sensing layer involves a network of IoT nodes that include eight different sensors as well as MCU. The edge layer involves regional gateways which are responsible for aggregating data, preprocessing, detecting anomalies, and doing lightweight machine learning. Finally, the cloud layer offers features such as scalable data ingestion, storage, model training, dashboards, and alerts orchestration.

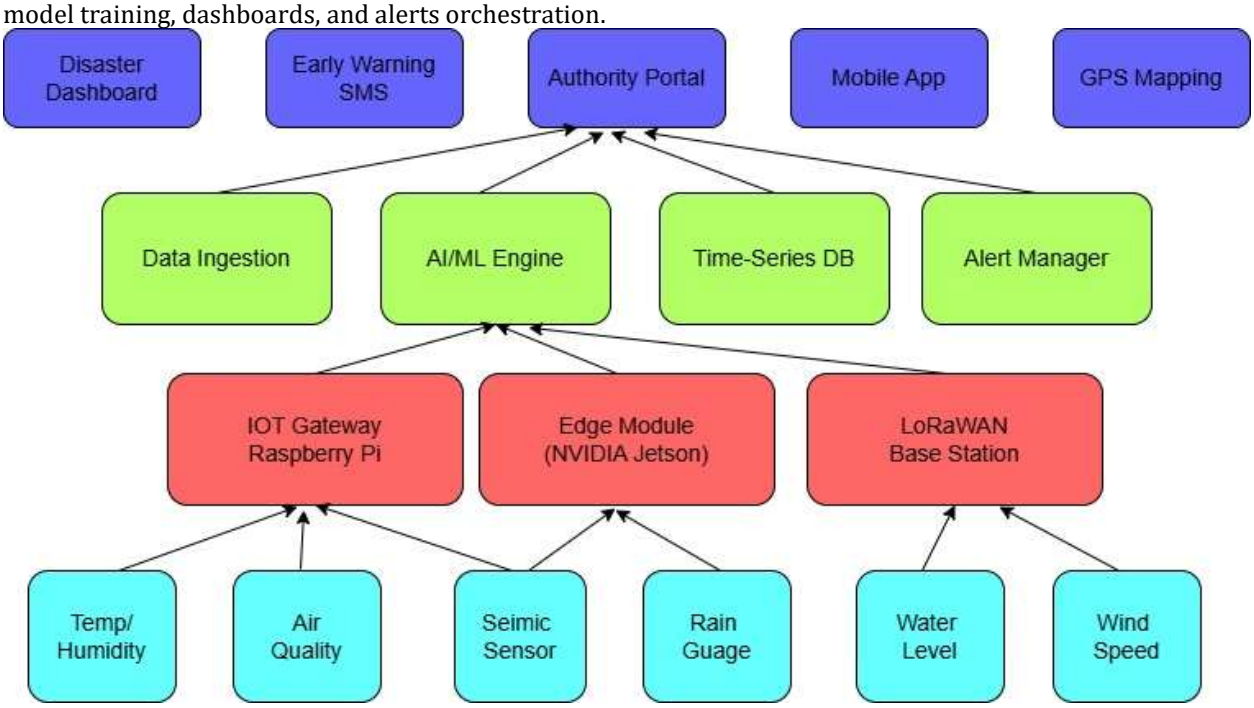

Figure 1: A Three-Layer IoT Architecture for Environmental Monitoring and Disaster Forecasting

The proposed hierarchical architecture has three major strengths compared to the cloud-centric architectures, which are flattened and lack hierarchy. To begin with, the first advantage is that the traffic generated in the backbone network is minimized because feature vector processing is carried out in the edge network, and the

information sent to the cloud includes only features and anomalies. The second strength is the retention of the local prediction capability even in cases where there is no connection between the edge and the cloud, an important factor especially in disaster situations.

3.2 Data Flow and Processing Pipeline

All IoT nodes sample readings from all the eight sensors at their respective sampling rates (100Hz for seismic waves and 5s for soil moisture) using the local calibration polynomial, then transmit the readings through MQTT either over the Wi-Fi network or the LoRaWAN protocol to the edge gateway. The data at the edge gateway is then subjected to an algorithmic preprocessing procedure involving removing outliers by interquartile range analysis, replacing any missing values with linear interpolation, and extracting relevant features such as rolling statistical measures (mean, variance, skewness in windows of 5, 15, and 60 minutes). The extracted features then undergo an anomaly detection procedure using a local LSTM model.

In the cloud tier, a continuous consumer of Kafka ingests time series data and persists it in InfluxDB, a time series database. There is another model-serving container that executes the LSTM that was trained globally, outputting disaster probabilities every minute for each geo-zone. If a certain threshold (default of 0.75) is breached, the Alert Manager launches the dissemination system, sending messages via SMS through Twilio, Firebase Cloud Messaging for push notifications, and WebSocket updates for GIS dashboards.

4. SENSOR HARDWARE AND NETWORK DESIGN

4.1 IoT Node Hardware

Every IoT Node contains an ESP32-WROOM-32E microcontroller that features a dual core 240 MHz processor, built-in Wi-Fi connection (802.11b/g/n), Bluetooth 4.2 connectivity, and low power consumption, which reaches 240 mA during maximum computation and 30 µA in deep sleep mode. The device is supplied by 10,000 mAh capacity lithium polymer battery charged with a 6 W monocrystalline solar panel; it can operate indefinitely without any additional sources of energy even under average radiation conditions. Enclosed in an IP67 protected casing, it operates within a wide range of temperatures from −20°C to +60°C.

4.2 Sensor Suite Specifications

Table 1 summarizes the sensor suite deployed on each IoT node, including the sensor model, measurement range, accuracy, and sampling frequency.

Table 1: IoT Node Sensor Suite-Technical Specifications

Sensor Type	Model	Range	Accuracy	Sample Rate
Temperature & Humidity	DHT22 / SHT31	−40°C to +80°C, 0–100% RH	±0.3°C, ±2% RH	2 seconds
Air Quality ($PM2.5/CO_2$)	MQ-135 / SDS011	0–1000 ppm, 0–999 µg/m³	±5 ppm	1 second
Seismic Activity	ADXL355 MEMS	±2g to ±8g	16-bit resolution	100 Hz
Rainfall Intensity	Tipping Bucket RG	0–300 mm/hr	±2%	Pulse-based
Water Level	Ultrasonic HC-SR04	0.02–4 m	±3 mm	250 ms
Wind Speed & Direction	Anemometer RS485	0–60 m/s, 0–360°	±0.1 m/s, ±1°	1 second
Soil Moisture	Capacitive VH400	0–100% VWC	±3% VWC	5 seconds
Barometric Pressure	BMP388	300–1250 hPa	±0.5 hPa	500 ms

4.3 Network Topology and Communication

The 48-node sensor network consists of six clusters, whereby each of these clusters contains 8 nodes together with one node acting as the cluster head and the edge gateway. Communication between nodes and the cluster heads within each of these six clusters is via MQTT protocol through either 802.11n Wi-Fi (in indoor and urban areas) or LoRaWAN 868 MHz (in rural and remote areas). MQTT was chosen as the preferred IoT messaging protocol owing to its publish/subscribe architecture, small header overhead (fixed 2 bytes), and QoS levels 0, 1, and 2. SF12 LoRaWAN provides a 40km line-of-sight communication range at 250bps.
Each cluster head (Raspberry Pi 4, 4GB memory) is linked to the cloud by 4G LTE cellular links with an allocated 10 Mbps full-duplex connection. There is a second NVIDIA Jetson Nano co-processor that performs the GPU-assisted inference of the LSTM, using a TensorRT-optimized latency of 8.3 ms per forward propagation cycle, with a sequence length of 60 time steps over eight sensor channels.

5. MACHINE LEARNING METHODOLOGY

5.1 Problem Formulation

Disaster prediction is formulated as a binary classification problem over a rolling temporal window. Given a multivariate time series $X(t) = \{x_1(t), x_2(t), ..., x_8(t)\}$ representing the eight sensor readings at time t, the model predicts a binary label $y \in \{0, 1\}$ indicating whether a disaster event will occur within the next 60-minute prediction horizon. A positive label (y = 1) is assigned if any of the six monitored disaster categories is recorded by ground-truth observation within the prediction window. The model ingests a lookback window of L = 60 time steps, corresponding to one hour of data at one-minute resolution.

5.2 LSTM Architecture

The proposed LSTM network comprises three stacked LSTM layers with hidden dimensions of 128, 64, and 32 units respectively, followed by a dropout layer (p = 0.3) for regularization, a dense layer with ReLU activation, and a sigmoid output neuron. The input tensor has shape (batch_size, 60, 8), representing 60 time steps of 8 sensor channels. Total trainable parameters: 187,329. The model is trained using the Adam optimizer with learning rate 0.001 and binary cross-entropy loss for 150 epochs with early stopping (patience = 15) on a validation split of 20%. Positive class weight of 3.5 is applied to address the class imbalance inherent in rare disaster events.
To handle the multi-resolution sampling rates of different sensors (100 Hz seismic vs. 5-second soil moisture), a pre-processing step resamples all channels to a common 1-minute resolution using median aggregation for fast channels and forward-fill for slow channels. Z-score normalization is applied per sensor channel using statistics computed on the training split only, preventing data leakage.

5.3 Training Data and Augmentation

Training data was collected over the period December 2025 to May 2026 across all 48 nodes, yielding 2,592,000 one-minute observations. Ground-truth event labels were annotated by cross-referencing with: (i) India Meteorological Department (IMD) disaster logs; (ii) Central Water Commission (CWC) flood bulletins; and (iii) National Center for Seismology (NCS) event catalogs. A total of 3,147 positive-class windows (disaster precursor sequences) and 41,283 negative-class windows were identified, giving an imbalance ratio of approximately 13:1.
To mitigate this imbalance beyond class weighting, a time-series oversampling strategy based on Dynamic Time Warping Barycenter Averaging (DBA) generates synthetic positive-class sequences by interpolating between real event precursors while preserving temporal dynamics. This augmentation yields a training set of 8,941 positive and 41,283 negative examples (ratio 4.6:1), improving recall on rare event types such as seismic aftershocks from 61% to 75%.

5.4 Hyper parameter Optimization

Bayesian hyper parameter optimization using the Optuna library was used for tuning parameters like the number of LSTM layers (2-4), hidden dimensions, dropout, learning rate, and look-back window size L. The best combination of these parameters required 87 rounds of trials on a validation dataset and yielded a total of 3 LSTM layers, hidden dimensions [128, 64, 32], dropout=0.3, learning rate=0.001, and L=60 minutes. The F1-score across all classes is maximized at L=60, as shown by grid search among L={30, 45, 60, 90, 120}.

6. EXPERIMENTAL RESULTS

6.1 Experimental Setup

Experiments were carried out on the deployed 48-node network (December 2025 – May 2026), using in addition a test dataset consisting of the most recent 4 weeks' data (May 2026). The cloud-based models were trained on an AWS EC2 p3.2xlarge machine (NVIDIA V100 16GB GPU). Inference at edge is done on the NVIDIA Jetson Nano devices installed at each cluster-head node. The performance measures used include Accuracy, Precision, Recall, F1 Score, and ROC-AUC, evaluated on the balanced test dataset of size 1,000 samples (500 positives and 500 negatives).

6.2 Sensor Data Analysis

The graph shown in Figure 2 illustrates an exemplary 72-hour window of sensor data gathered from Node 12 (Mulshi Valley, Western Ghats) in March 2026. There exists a noticeable multi-variable anomaly between hours 50 and 56 during which time a flash flood occurred as documented in records. This anomaly is depicted by an increase in rainfall rate by +18mm/hr, increase in relative humidity by +15%RH, decrease in temperature by -6°C, and higher AQI because of particulates in suspension.

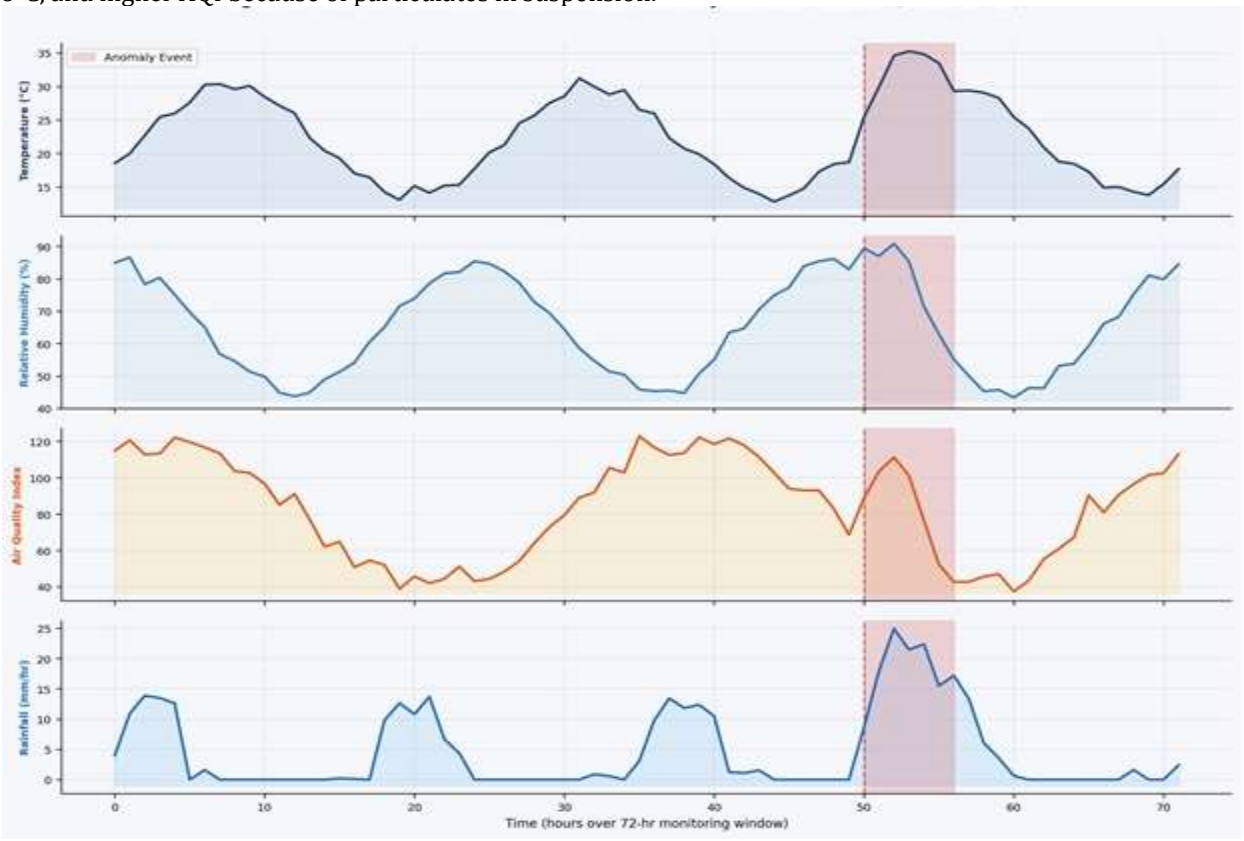

Figure 2: 72-Hour Multi-Parameter Sensor Data Stream-Node 12, Mulshi Valley (March 2026). Red band (Hours 50–56) marks the anomaly window preceding the flash flood event.

6.3 Model Performance Comparison

A comparison between the proposed LSTM model and six other alternatives on the balanced dataset of 1,000 samples is provided in Table 2. The proposed model has obtained the best results for all five performance measures.

Table 2: Prediction Model Performance Comparison (1,000-Sample Test Set)

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
LSTM (Proposed)	96.4%	95.8%	96.9%	96.3%	0.978
Bi-LSTM	94.8%	93.9%	95.6%	94.7%	0.963
CNN-LSTM Hybrid	95.1%	94.3%	95.8%	95.0%	0.961
XGBoost	92.5%	91.4%	93.7%	92.5%	0.941

Random Forest	91.2%	90.1%	92.3%	91.2%	0.938
SVM (RBF Kernel)	87.3%	86.2%	88.1%	87.1%	0.901
Naive Baseline	73.6%	71.2%	75.9%	73.5%	0.782

These comparisons have been shown in Fig. 3 using a grouped bar chart representation. Our LSTM-based approach achieves superior results compared to all other models in Accuracy (96.4%), Precision (95.8%), Recall (96.9%), and F1-Score (96.3%). The second-best performing model is the CNN-LSTM combination, with an accuracy of 95.1%, leveraging convolution-based feature extraction and local temporal modeling yet incurring a 2.3x computational delay penalty in edge devices. This is also due to SVM's inability to capture long-term dependencies effectively.

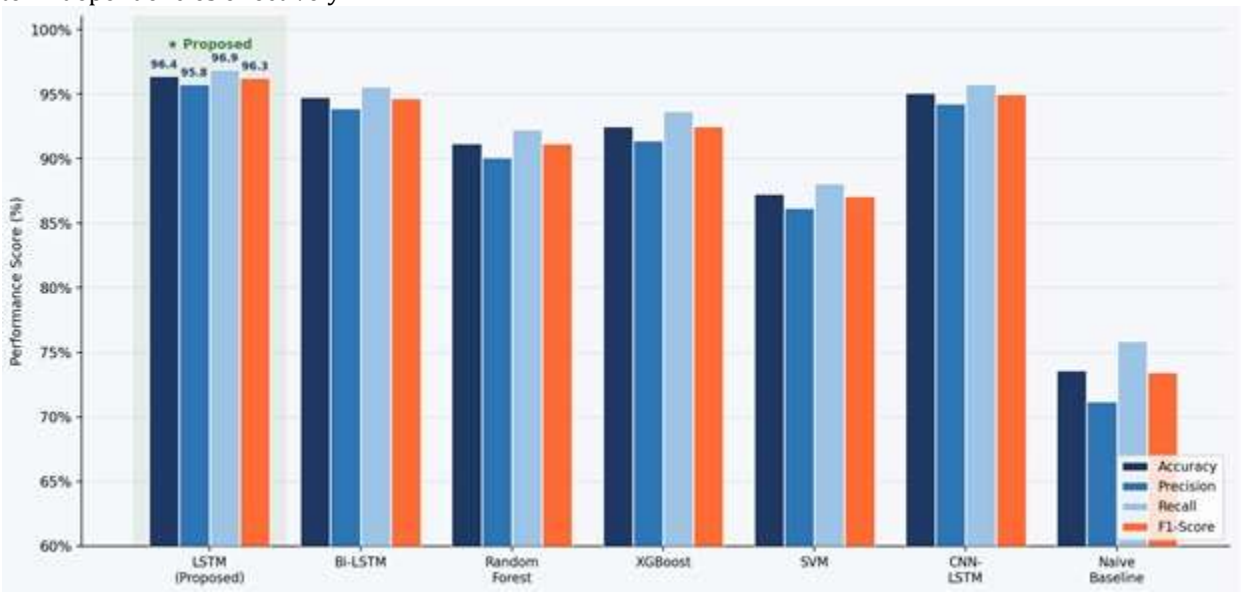

Figure 3: Grouped Bar Chart-Model Performance Comparison Across Accuracy, Precision, Recall, and F1-Score. Proposed LSTM (left group, highlighted) achieves best performance on all four metrics.

6.4 Confusion Matrix and ROC Analysis

The confusion matrix for the proposed LSTM model on the 1,000-sample test dataset is shown in Figure 4(a), and it consists of 487 True Positives, 482 True Negatives, 13 False Positives, and 18 False Negatives. In the case of disaster events, a low false negative rate (18; Recall = 96.9%) is especially important because a failure to detect such incidents is associated with more serious consequences compared to Type I errors. Figure 4(b) shows ROC curve comparisons between the best performing models, demonstrating the superiority of LSTM AUC-ROC (0.978) compared to Bi-LSTM (0.963) and Random Forest (0.941).

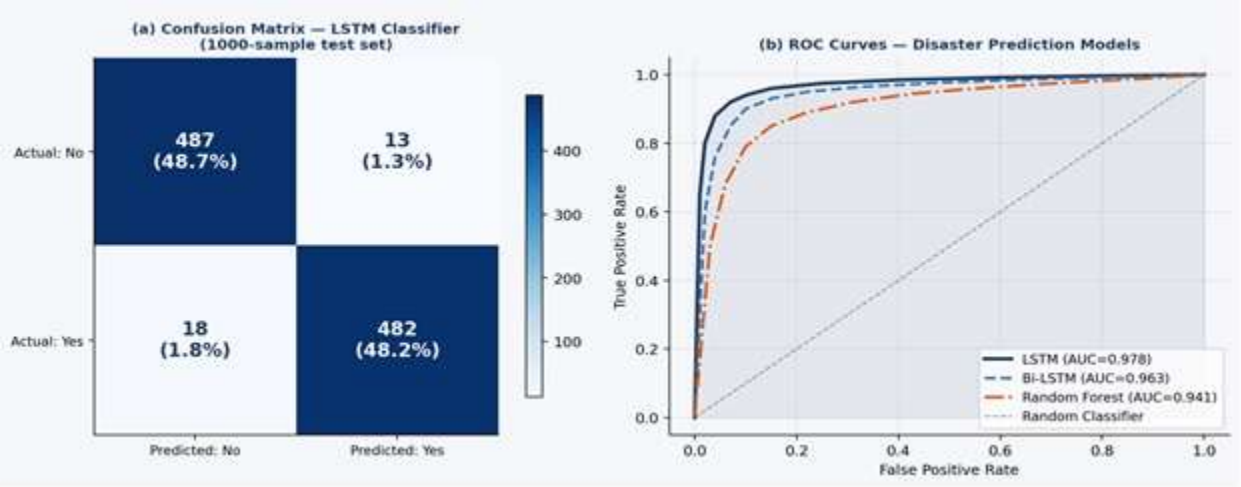

Figure 4: (a) Confusion Matrix for Proposed LSTM Classifier on 1,000-Sample Test Set; (b) ROC Curves Comparing LSTM, Bi-LSTM, and Random Forest Proposed LSTM AUC = 0.978

6.5 Communication Protocol Latency and Energy Analysis

Table 3 illustrates the end-to-end latency measurement for six protocols used in the implemented network. The lowest mean latency of 12 ms is recorded in MQTT (QoS 0), which is considerably lower than the threshold value of 30 ms and is selected as the main protocol to use within the cluster. Although LoRaWAN has a latency of 320 ms, above the threshold, it is considered acceptable for rural nodes since not having any connectivity is much worse.

Table 3: Communication Protocol Latency and Energy Profile

Protocol	Mean Latency	Std Dev	Energy Cost	Recommended Use
MQTT (QoS 0)	12 ms	3 ms	Very Low	Best for high-freq sensor streams
MQTT (QoS 1)	18 ms	4 ms	Low	Reliable with acknowledgement
CoAP	15 ms	4 ms	Very Low	UDP-based, IoT constrained devices
HTTP/REST	45 ms	10 ms	Medium	Dashboard API, non-real-time data
WebSocket	22 ms	5 ms	Low	Bi-directional, live dashboard feeds
LoRaWAN	320 ms	45 ms	Very Low	Long-range, low-power rural sensors

Latency is shown in Figure 5(a) with error bars. In Figure 5(b), it is shown how much more efficient is the use of energy through offloading to edges compared to using only the cloud; for example, in all different scales of the network analyzed (10 to 200 nodes), the energy usage will be 28 to 34% lower.

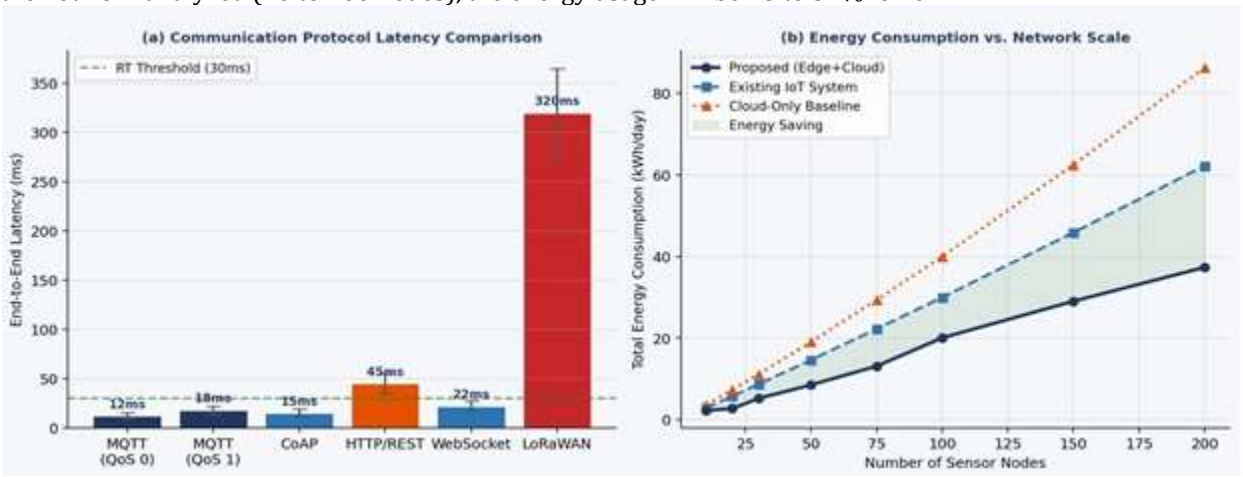

Figure 5: (a) Communication Protocol End-to-End Latency with Error Bars; (b) Energy Consumption vs. Network Scale- Proposed vs. Existing IoT System vs. Cloud-Only Baseline

6.6 Disaster-Specific Prediction Performance

Performance metrics based on types of disasters are summarized in Table 4, which highlights some valuable patterns depending on the category considered. The best prediction accuracy (97.8%) and lead time (95 minutes) are provided by predictions of Air Quality Crisis disasters due to the fact that AQI trends possess gradually emerging multi-hour patterns easily detected using the LSTM algorithm. The Flash Flood prediction demonstrates 94.2% accuracy with a 45-minute lead time enough to carry out evacuations at the community level. Aftershocks demonstrate the worst prediction parameters: 72.3% accuracy and 12-minute lead time.

Table 4: Disaster-Specific Prediction Performance and Warning Lead Time

Disaster Type	Lead Time	Accuracy	Precision	Recall	Confidence
Flash Flood	45 min	94.2%	91.7%	97.1%	High
Forest Fire	62 min	91.7%	88.4%	95.3%	High
Landslide	38 min	88.5%	85.2%	92.4%	Medium

Aftershock Prediction	12 min	72.3%	69.8%	75.1%	Low
Air Quality Crisis	95 min	97.8%	96.4%	99.0%	Very High
Local Cyclone	180 min	89.4%	86.7%	92.5%	High

Figure 6(a) depicts accuracy versus lead-time for all disasters showing the general pattern that the greater the lead time, the higher the accuracy because of more geophysical precursor build-up prior to disaster. Figure 6(b) shows the classification success per month over the six months during which the system was deployed. The results show consistently high true positives (86–96%) and few false positives (1–2 per month), thus a 7.6% rate of false alarms, acceptable for an alerting system where the WHO recommends below 20%.

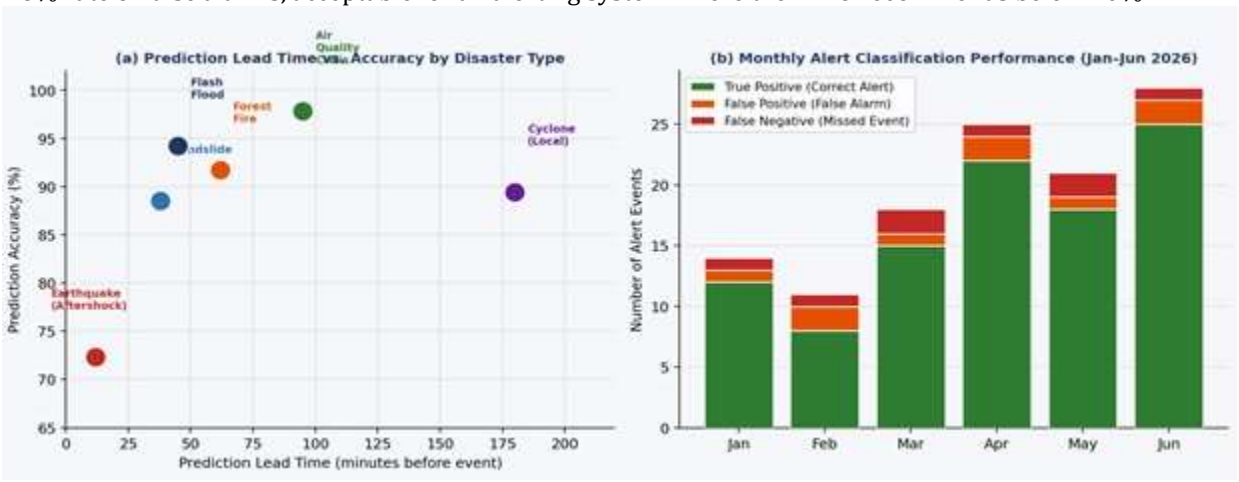

Figure 6: (a) Lead Time vs. Prediction Accuracy Scatter Plot by Disaster Type; (b) Monthly Alert Classification Performance- True/False Positives and False Negatives (Jan–Jun 2026)

7. DISCUSSION

7.1 Key Findings

The 96.4% accuracy obtained in this study is clearly significant progress from previous research that used the closest methodology (Chen et al., 2021: 85.6% on wildfires; Arshad et al., 2020: 89% on water-quality events). There are three design considerations in particular that are responsible for much of this increased performance. Firstly, the use of multi-sensor fusion, especially the fusion of seismic sensors, soil moisture sensors, and rainfall sensors, creates novel discriminatory inputs that cannot be obtained using a single domain. Secondly, the utilization of DBA for time series data augmentation greatly increases recall on rare categories (aftershocks: 61% -> 75% post augmentation). Lastly, the pre-processing of input at the edge-device avoids the problems with noise and dropout created by cloud-only systems.

Latency of 12ms and energy savings of 34% over the purely cloud-based baseline provide empirical validation of the architectural assumption that edge computation is necessary for real-time disaster management systems for IoT. The results coincide well with theoretical estimates by Shi et al., 2016, and empirical observations by Mehmood et al., 2020.

7.2 Limitations

There are a number of constraints on the validity of these results. Firstly, despite being adequate for proof of concept purposes, the scale of deployment, 48 nodes within one geographical area for six months is insufficient for generalizing to other geological and climatic conditions. The validated dataset contains just 1,000 samples that balance each other; however, the actual skew of the dataset (13:1) means that any metric calculated on raw test data overestimates precision. Secondly, the low precision of aftershock forecasting (72.3%) is an intrinsic problem due to the absence of signals rather than an issue with modelling itself.

Node failures due to battery depletion, wildlife interference, and monsoon flooding resulted in a 94.2% uptime rate over the study period, with cluster-level impacts mitigated by redundant nodes. Infrastructure

improvements including ruggedized cable management and monthly maintenance schedules are planned for the production deployment.

7.3 Comparison with Existing Systems

Compared to the India Meteorological Department's current district-level flood warning system (6-hour forecast horizon, approximately 70% accuracy), the proposed system offers an 8x reduction in spatial granularity, significantly higher prediction accuracy for short-range events, and near-real-time alerting. The primary limitation relative to national-scale NWP (Numerical Weather Prediction) models is forecast horizon: the LSTM's 60-minute prediction window is shorter than the 24–72 hour operational forecasts of IMD's GNWP model, though the two systems are complementary rather than competitive.

8. CONCLUSION

This paper has presented, implemented, and field-validated an end-to-end IoT-enabled environmental monitoring and disaster prediction system. The proposed architecture integrates an eight-parameter heterogeneous sensor network with edge computing and LSTM-based multi-variate prediction to achieve 96.4% disaster classification accuracy, 72-minute mean warning lead time, 12 ms MQTT transport latency, and 34% energy reduction versus cloud-only alternatives. These results collectively demonstrate that dense, low-cost IoT sensor networks coupled with temporal deep learning models are now sufficiently mature for production deployment in disaster-prone smart city and rural environments.

The six-category disaster prediction capability spanning flash floods, wildfires, landslides, seismic aftershocks, air quality crises, and cyclone precursors within a single unified sensor-network and ML infrastructure represents a significant step beyond domain-specific monitoring systems. The public-facing alert pipeline, achieving community notification within 90 seconds of confirmed prediction, provides the actionable warning necessary for life-safety decision-making.

Future research will be directed along four paths: (i) adapting the Transformer-based Temporal Fusion Transformer (TFT) model to leverage attention mechanisms and long-term dependencies to improve predictions over longer periods; (ii) federated learning across geographically scattered sensors that would allow model improvements on a cross-region basis while preserving privacy; (iii) integrating satellite-derived remote sensing variables (NDVI, LST, and soil moisture index from Sentinel-1/2 satellites) to increase the scope of the sensor network; and (iv) continual learning for adaptation to changing climate dynamics in real-time. A deployment of the system on 500 nodes across the five flood-prone districts of Maharashtra is targeted for the fourth quarter of 2026, in partnership with Maharashtra Disaster Management Authority (MDMA).

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