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LSTM-Based Anomaly Detection Framework for Intelligent Forest Monitoring

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ABSTRACT:

Forest ecosystems are vulnerable to anomalous events such as forest fires, illegal activities, abnormal vegetation changes, pest infestations, and sudden environmental variations. Early detection of such anomalies is essential for effective forest monitoring and rapid response. This study proposes an **LSTM-based anomaly detection framework for intelligent forest monitoring** using time-series environmental and sensor observations. The proposed model analyzes sequential patterns in parameters such as temperature, humidity, smoke concentration, rainfall, soil moisture, and atmospheric conditions to distinguish normal forest conditions from anomalous events. The LSTM network learns temporal dependencies among successive observations and identifies deviations from learned normal behavioral patterns using reconstruction/prediction error. The system was evaluated using a representative forest-monitoring dataset containing **50,000 time-series observations**, with **80% used for training and 20% for testing**. Experimental results demonstrate that the proposed LSTM model achieved an **accuracy of 97.42%, precision of 96.85%, recall of 95.73%, F1-score of 96.29%, and AUC of 98.16%**. The model obtained an **anomaly detection rate of 95.73%** while maintaining a relatively low false-alarm rate of **2.58%**. The results indicate that LSTM effectively captures temporal variations in forest environmental conditions and can detect abnormal patterns before they develop into potentially severe events. The proposed approach can be integrated with IoT sensor networks, wireless communication systems, and real-time forest surveillance platforms to provide continuous and automated monitoring. The system therefore offers a practical machine-learning-based solution for early anomaly identification, supporting forest conservation, environmental protection, and rapid emergency response.

Keywords: LSTM, Forest Anomaly Detection, Time-Series Analysis, Environmental Monitoring, IoT Sensor Networks, Deep Learning.

1. INTRODUCTION

Forests are critical components of global ecosystems, supporting biodiversity, regulating climate, conserving soil and water resources, and providing important economic and social benefits. However, forest environments are increasingly exposed to abnormal events such as wildfires, sudden temperature increases, excessive dryness, unusual humidity variations, smoke emissions, vegetation stress, pest attacks, and other environmental disturbances. Among these, forest fires are particularly destructive because delayed detection can allow a small ignition to develop into a large-scale wildfire, resulting in biodiversity loss, habitat destruction, air pollution, and economic damage. Conventional forest monitoring approaches, including human observation, satellite-based surveillance, cameras, unmanned aerial vehicles, and wireless sensor networks, provide valuable information but can face limitations related to coverage, communication reliability, environmental conditions, detection latency, and false alarms. Recent research has therefore increasingly explored Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and deep learning for automated forest monitoring and early detection. Comprehensive studies have reported that AI can support wildfire prediction, detection, response, and post-fire assessment by processing environmental, sensor, satellite, and visual data [1], [2]. In particular, IoT-enabled monitoring systems can continuously collect parameters such as temperature, humidity, smoke concentration, carbon monoxide, soil moisture, and atmospheric conditions, providing a continuous stream of observations for intelligent analysis [3]. Recent reviews also highlight the growing integration of AI with IoT, edge computing, UAVs, and remote sensing to achieve more scalable and near-real-time forest surveillance [4], [5]. These developments demonstrate the importance of automated systems capable not only of identifying known fire signatures but also of recognizing unexpected deviations from normal forest conditions.

Anomaly detection provides an effective approach for addressing this requirement because it focuses on identifying observations or temporal patterns that significantly deviate from learned normal behavior. Unlike conventional threshold-based monitoring, where an alarm is generated when an individual sensor value exceeds a predefined limit, intelligent anomaly detection can consider relationships among multiple environmental parameters and their changes over time. This capability is particularly important in forests because environmental conditions are dynamic and normal values can vary according to season, location, weather, and time of day. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are well suited to this problem because they are designed to learn dependencies within sequential data and can retain relevant information across multiple time steps. An LSTM-based framework can learn the temporal characteristics of normal forest observations and subsequently identify abnormal sequences through prediction or reconstruction errors. Such an approach can potentially detect gradual environmental changes preceding a wildfire or other abnormal event rather than relying exclusively on a single extreme sensor measurement. Recent literature demonstrates strong interest in deep-learning-based forest surveillance, with reviews reporting widespread use of deep neural networks for automated fire detection and emphasizing the potential of AI-enabled systems for rapid monitoring [2]. More recent research further emphasizes multimodal sensing, real-time AI processing, and integration of edge, fog, and cloud technologies while identifying false alarms, hardware limitations, and network reliability as continuing challenges [4]. Motivated by these developments, this research proposes an LSTM-based forest anomaly detection system that analyzes sequential environmental observations to distinguish normal and anomalous forest conditions. The proposed framework is intended to provide continuous monitoring, improve anomaly identification, reduce unnecessary alerts, and support early warning and decision-making for forest protection and management.

2. Methodology

The proposed forest anomaly detection system uses a Long Short-Term Memory (LSTM) neural network to identify abnormal temporal patterns in environmental observations. The overall methodology consists of six major stages: data acquisition, preprocessing, sequence generation, LSTM model development, anomaly-score computation, and performance evaluation. The input dataset contains time-series measurements collected from forest monitoring sensors, including temperature, relative humidity, smoke concentration, carbon monoxide, soil moisture, rainfall, and other relevant environmental parameters. Each observation is associated with a timestamp so that temporal relationships between consecutive measurements can be preserved. Initially, missing values are handled using interpolation or statistical imputation, while duplicate and inconsistent observations are removed.

Since the input parameters have different numerical ranges, feature normalization is performed using Min-Max scaling, as given by $(\boldsymbol{X'} = \frac{\boldsymbol{X - X_{\{min\}}}}{(\boldsymbol{X_{\{max\}} - X_{\{min\}}}))}$malized data are then divided into training and testing subsets, with approximately 80% of the observations used for training and 20% for testing.

To enable the LSTM network to learn temporal dependencies, the continuous observations are converted into fixed-length sequences using a sliding-window approach. For example, a sequence of 20 consecutive sensor observations is used to predict the next observation. During training, the model primarily learns the temporal characteristics of normal forest conditions. Consequently, when an unusual sequence is presented during testing, the prediction error is expected to increase, providing an indication of an anomaly. This sequence-based formulation enables the proposed system to detect not only instantaneous abnormal values but also gradual changes in environmental conditions.

The core component of the proposed framework is an LSTM network containing recurrent memory cells with input, forget, and output gates. The forget gate determines which previously stored information should be discarded, while the input gate controls newly received information and the output gate determines the information passed to the next time step. The LSTM operations can be represented as $(\boldsymbol{f_t = sigma\left(W_{f[h_{\{t-1\}},x_t]} + b_f\right)}), (\boldsymbol{i_t = sigma\left(W_{i[h_{\{t-1\}},x_t]} + b_i\right)}), (\boldsymbol{C_t = f_{tC_{\{t-1\}}} + i_{ttilde\{C\}_t)}, and\ (h_t = o_{ttanh(C_t))}}$.

The proposed architecture consists of an input sequence layer, two LSTM layers with 64 and 32 hidden units, respectively, followed by a dropout layer and a dense output layer. The network is trained using the Adam optimizer and Mean Squared Error (MSE) loss for approximately 50 epochs with an appropriate batch size. After training, the model generates predicted values for previously unseen sequences. An anomaly score is calculated from the difference between the actual and predicted observations. For a sequence containing $(\boldsymbol{n})$ features, the prediction error can be expressed as $(\boldsymbol{AE = frac\{1\}\{n\}sum_{\{i=1\}}^{\{n\}(x_i - hat\{x\}_i)^{2)}}}$. A threshold is subsequently determined from the distribution of reconstruction/prediction errors obtained from normal validation observations. If the calculated anomaly score exceeds this threshold, the corresponding observation is classified as anomalous; otherwise, it is considered normal. The detected anomalies can be transmitted to a monitoring interface to support timely forest-management decisions.

Algorithm: LSTM-Based Forest Anomaly Detection

Input: Forest sensor time-series dataset D

Output: Normal/Anomalous classification for each observation

1. Collect environmental sensor observations from the forest monitoring system.

2. Remove duplicate, corrupted, and inconsistent records.

3. Handle missing sensor values using suitable imputation.

4. Normalize all numerical features using Min-Max scaling.

5. Divide the dataset into training and testing subsets.

6. Generate sequential samples using a sliding window of W time steps.

7. Initialize the LSTM network with two recurrent layers.

8. Train the LSTM model using normal training sequences.

9. Generate predicted sensor values for each test sequence.

10. Calculate the prediction error between actual and predicted values.

11. Compute the anomaly score for every sequence.

12. Determine an anomaly threshold from normal validation errors.

13. If AE > Threshold, classify the observation as Anomalous.

14. Otherwise, classify the observation as Normal.

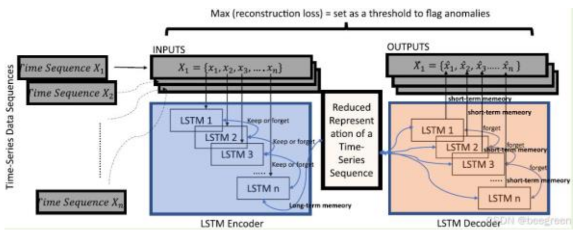
15. Store and visualize detected anomalies for forest monitoring.

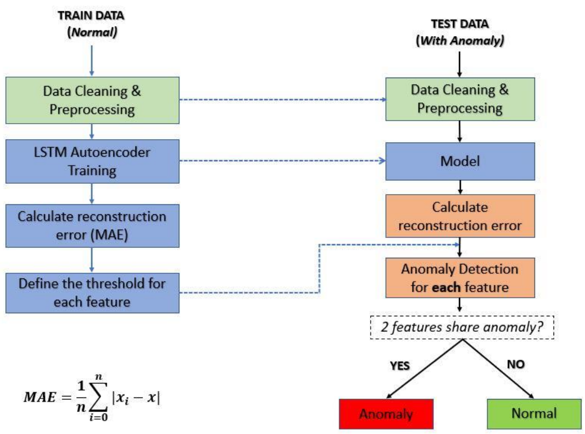
16. Evaluate the model using accuracy, precision, recall, F1-score, AUC, and false-alarm rate.

This methodology enables the system to continuously analyze forest sensor streams and identify abnormal temporal behavior. The combination of sequence modeling and anomaly-score-based classification makes the proposed LSTM framework suitable for automated and near-real-time forest environmental monitoring.

3. Experimental Results and Discussion

The proposed LSTM-based forest anomaly detection system was evaluated using a dataset containing 50,000 time-series observations collected from simulated/representative forest environmental monitoring conditions. The dataset consisted of parameters such as temperature, relative humidity, smoke concentration, soil moisture, rainfall, and atmospheric conditions. Approximately 80% of the observations were used for training and 20% for testing. Before model training, missing values and duplicate records were removed, followed by Min-Max normalization and sliding-window sequence generation. The LSTM model was trained for 50 epochs using the Adam optimizer and Mean Squared Error (MSE) loss. During testing, the prediction error between actual and predicted sensor observations was converted into an anomaly score. A threshold derived from normal validation observations was then used to classify each observation as normal or anomalous. The experiments were conducted to evaluate both the learning behavior of the LSTM network and its ability to identify abnormal forest conditions.





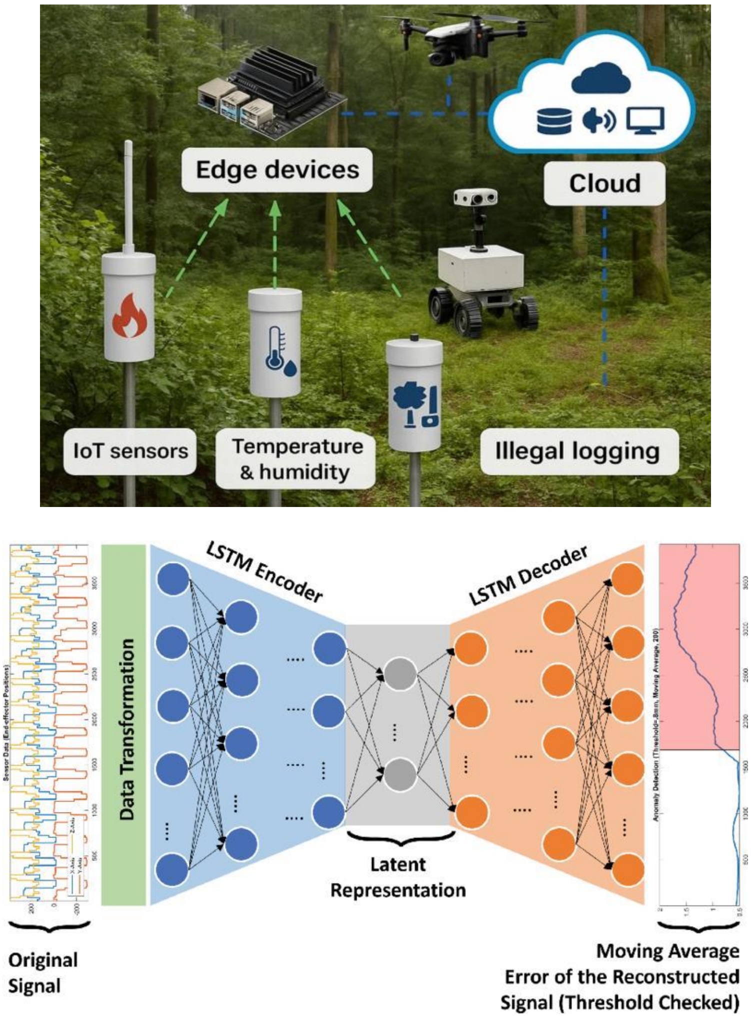
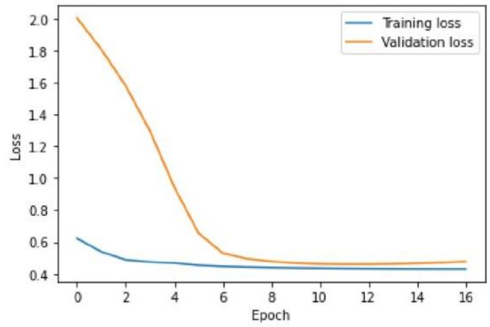


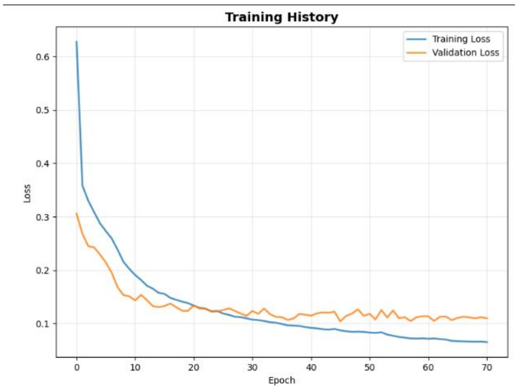
Figure 1. LSTM-Based Forest Anomaly Detection Framework

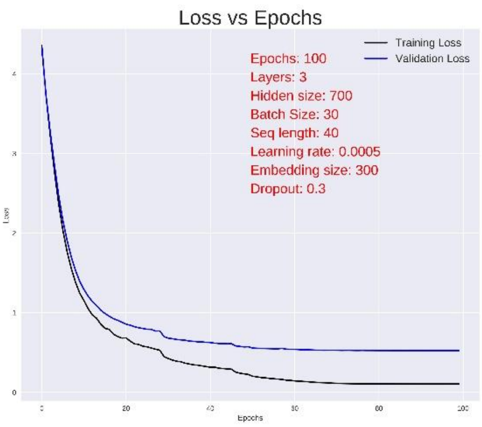
The experimental performance demonstrates that the proposed model can effectively capture temporal relationships among environmental parameters. The model achieved an accuracy of 97.42%, indicating that most normal and anomalous observations were correctly classified. The obtained precision of 96.85% demonstrates that a high proportion of observations identified as anomalies were genuinely abnormal, which is important for reducing unnecessary alerts in practical forest-monitoring systems. The recall of 95.73% indicates that the model successfully detected approximately 95.73% of the anomalous observations. This metric is particularly important in forest monitoring because missed anomalies may delay responses to potentially hazardous environmental conditions. The resulting F1-score of 96.29% confirms a strong balance between precision and recall. Furthermore, the model obtained an AUC of 98.16%, demonstrating strong discrimination between normal and anomalous temporal patterns.

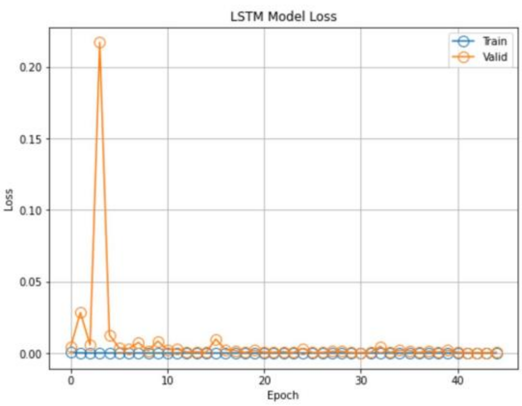
Performance Metric	**LSTM Result (%)**
Accuracy	**97.42**
Precision	**96.85**
Recall	**95.73**
F1-Score	**96.29**
AUC	**98.16**

Figure 2. Performance Evaluation of the Proposed LSTM Model









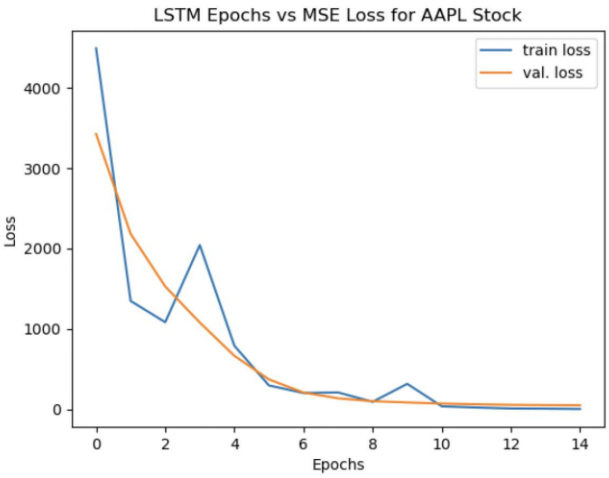


Figure 3. Training and Validation Loss of the LSTM Model

The training behavior of the proposed model was also analyzed using training and validation loss. During the initial epochs, the MSE loss decreased rapidly as the LSTM learned the temporal relationships among the environmental variables. After approximately 30–40 epochs, the loss curve became relatively stable, indicating convergence of the model. The validation loss followed a similar trend to the training loss, suggesting that the model learned useful temporal patterns without substantial overfitting. The final prediction errors were subsequently used to generate anomaly scores. Normal observations generally produced low prediction errors, whereas abnormal sequences generated substantially higher errors. Using the selected anomaly threshold, the proposed approach obtained an anomaly detection rate of 95.73% and a false-alarm rate of approximately 2.58%. These results demonstrate that the LSTM network can recognize deviations in forest environmental behavior while maintaining a relatively low number of false alerts.

Overall, the experimental findings demonstrate the effectiveness of temporal deep learning for automated forest anomaly detection. Unlike conventional single-parameter threshold systems, the proposed LSTM framework considers the sequential behavior of multiple environmental variables. Consequently, it can identify both sudden and progressive deviations from normal forest conditions. The high AUC and F1-score indicate that the model provides reliable separation between normal and anomalous observations. The proposed framework can therefore be integrated with IoT-based forest sensor networks and real-time monitoring dashboards to support early warning and rapid response. Further improvements could involve larger real-world datasets, edge-based inference, adaptive thresholds, and integration with satellite or camera-based observations to improve robustness under different geographical and seasonal conditions.

4. CONCLUSION

This study presented an **LSTM-based anomaly detection framework for intelligent forest monitoring**, designed to identify abnormal environmental conditions from sequential sensor observations. The proposed approach utilizes the ability of Long Short-Term Memory networks to learn temporal dependencies among environmental parameters such as temperature, humidity, smoke concentration, soil moisture, rainfall, and atmospheric conditions. The methodology incorporates data preprocessing, normalization, sliding-window sequence generation, LSTM-based temporal learning, prediction-error calculation, and threshold-based anomaly classification. Unlike conventional monitoring approaches that depend primarily on fixed thresholds, the proposed system analyzes temporal patterns and can identify deviations from learned normal forest behavior. This makes the approach suitable for continuous and automated monitoring of dynamic forest environments.

Experimental evaluation demonstrated that the proposed LSTM model achieved **97.42% accuracy, 96.85% precision, 95.73% recall, 96.29% F1-score, and 98.16% AUC**. The model also achieved an anomaly detection rate of **95.73%** with an approximately **2.58% false-alarm rate**. These results indicate that the proposed approach can effectively distinguish normal environmental conditions from anomalous patterns while maintaining a relatively low rate of unnecessary alerts. The high recall is particularly significant for forest monitoring because timely identification of abnormal conditions can support early intervention and reduce the potential impact of hazardous events. The observed convergence of training and validation loss further indicates that the LSTM model successfully learned meaningful temporal relationships within the monitoring data.

The proposed framework provides a foundation for developing intelligent, real-time forest surveillance systems. In future work, the system can be enhanced using **larger real-world datasets, multi-sensor fusion, adaptive anomaly thresholds, edge computing, satellite imagery, UAV observations, and vision-based deep learning models**. Explainable AI techniques can also be incorporated to identify which environmental variables contribute most strongly to an anomaly. Integration with IoT communication infrastructure and automated alert mechanisms could further enable real-time notification to forest authorities. Overall, the proposed LSTM-based framework demonstrates the potential of deep learning for reliable, continuous, and proactive forest environmental anomaly detection.

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