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An Intelligent Environment Monitoring System Using Wireless Sensor Network (WSN) And Machine Learning For Real-Time Detection Of Forest Fire

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Abstract: The issues of forest fires pose a significant environmental threat which usually leads to loss of biodiversity, destruction of property and air pollution. This study proposes an intelligent environment monitoring system using Wireless Sensor Network (WSN) integrated with Recurrent Neural Network (RNN) model for real-time detection of forest fire. The data-set used for training the RNN algorithm is the Environmental Sensor Telemetry Data (ESTD) data-set from Kaggle data-set repository. The data-set was further pre-processed through data cleaning, normalization and the use of Synthetic Minority Oversampling Technique (SMOTE) for handling data imbalance. The RNN model presented is made up of 3 hidden layers with Tanh activation function and an output layer with Sigmoid activation function for binary classification of either there is forest fire or not. Google Colab development environment was used for implementation of the model and performance evaluation results of the system presented that the model attained an accuracy of 94.3%, precision of 0.9320, recall of 0.9417 and F1-score of 0.9368. The results indicates that the model is reliable and that the application of AI-driven WSN systems can be used to enhance early wildfire detection and environmental monitoring. Finally, future research could consider hyperparameter optimization, additional environmental factors and real-world deployment to further improve detection accuracy.

Keywords: WSN; Environment Monitoring; Forest Fire Detection; RNN; Machine Learning

1. INTRODUCTION

In the literature, wireless sensor networks (WSN) are frequently offered as a way to implement extensive autonomous monitoring systems [1,2]. Usually, a Base Station (BS) and several Sensor Nodes (SN) dispersed throughout an area of interest make up these systems. The SN gathers the physical characteristics of the surrounding environment, while the BS gathers, aggregates, and evaluates data from every node. These networks actually arose out of the need for collaborative monitoring solutions, specifically for hazard detection [3-5], health and quality of life [6-9], security [10,11], and environmental [12-14].

Temperature, sound, vibration, acceleration, pressure, motion, humidity, and the concentrations of chemicals or pollutants from diverse application areas are just a few of the environmental parameters that WSNs may measure. Under these circumstances, WSNs work together to send data to a central location, or sink, where it may be seen and examined [15]. Without human assistance, wireless sensor nodes can function in their deployed context and endure severe environmental conditions. Large geographic regions can be covered by wireless sensor nodes that are either movable (dynamic deployment) or set in situ (static deployment) [16].

Environmental Monitoring Applications (EMAs) provide special difficulties that might compromise service quality if they are not taken into account while deploying them. For example, even in locations with moderate spatiotemporal variability, the data obtained may be impacted by the deployment of nodes in highly dynamic surroundings. These alterations might result from abrupt weather shifts or nearby human activity [17,18]. Therefore, real-time environmental monitoring is essential, but it doesn't have to be expensive or time-consuming to produce even better results than traditional monitoring systems. Traditional monitoring methods scan and keep an eye on the soil, air, and water using sedimentation, electrostatic sampling, absorption, filtration, and condensation [19].

Forest fires have become a major worldwide security risk because they destroy both human populations and forest ecosystems. Among other negative effects, such destruction can cause the greenhouse effect and changes in the climate. One interesting fact is that most forest fires are caused by people. As a result, early identification of forest fires is essential to minimising the damage caused by these fires. To enable the delivery of these new services, WSNs and similar sensing technologies have to be installed across the city. Despite their variable and occasionally very short ranges, these sensors self-organise into ad hoc networks once they are deployed, ensuring global connection [20]. Once placed and configured, these sensors can monitor a wide range of data, including motion, temperature, humidity, and fire detection, allowing for prompt safety actions to be performed [21]. When they detect motion, they can even initiate additional activities, either directly or indirectly, such as turning on a light. WSNs are made up of tiny, light, inexpensive, and low-powered sensor nodes [21,22]. These nodes have the ability to gather, analyse, and aggregate sensor data before sending it straight to the Base Station (BS) over the wireless channel or relaying it to the BS through nearby nodes [23].

In order to monitor physical or environmental conditions, WSNs are self-configured, infrastructure-free wireless networks that transmit data to a specific location or sink for observation and analysis [24].

The two main benefits of a WSN are its efficiency and low power consumption [25]. The proposed detection system presented in this study uses a microcontroller, transceiver module, and power components to deploy wireless sensor nodes in accordance with cellular architecture, covering the entire area with sensors to monitor temperature, relative humidity, light intensity level, and Carbon Monoxide (CO) level. A predefined threshold ratio and a continually computed ratio in real time are used to verify the sensor readings for each parameter. Only ratios that surpass the preset ratio are transmitted from the sensor node to the base station for additional analytical processing. The network and the secondary analysis procedure are connected via the gateway node, which is an interface. To improve detection accuracy, threshold ratio analysis and a machine learning regression model were employed in the analysis procedure. Data from fire and non-fire scenarios in various locations and climates were gathered for the model's training and testing.

2. THE PROPOSED SYSTEM METHOD

In this study, the use of WSN technology to collect environmental data monitoring factors such as monitor temperature, smoke relative humidity, light intensity level, and CO or CO_2 level using a microcontroller, transceiver module, and power components of the WSN sensor module. The collected data is transmitted to through the network cluster to the network gateway node or Base Station (BS) where a machine learning model (Recurrent Neural Network (RNN)) is deployed for analysis of the data and detection of forest fire in the environment. The system is implemented by training the proposed RNN algorithm on Google Colab environment before being deployed to a network architecture for integration. The performance of the generated RNN model is further evaluated and the results are discussed further in the work. The architectural design of the proposed system is presented in Figure 1.

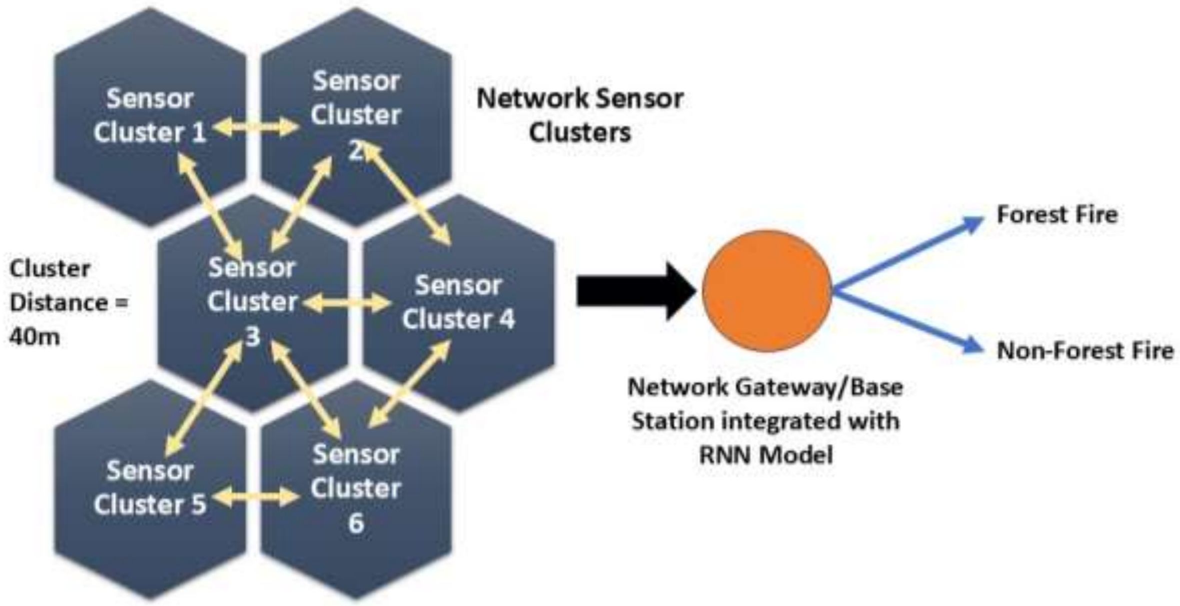

Figure 1: The Architecture of the Proposed System

In Figure 1, the architecture of the system is shown with the sensors deployed with 40meter distance from each other. The sensor nodes have direct communication within themselves where the final compilation of the data acquired is sent to the network gateway node. The gateway is integrated with the proposed machine learning model which is used to analyse the data collected to make final decision on the activities going on in the environment.

2.1 Data Collection

The data that has been used for the implementation of the proposed machine learning model is the Environmental Sensor Telemetry Data (ESTD) acquired from Kaggle dataset repository. Three identical, specially constructed, breadboard-based sensor arrays produced the data. Every array had a Raspberry Pi device attached to it. A real site with a range of climatic variables was chosen for each of the three Internet of Things (IoT) devices. Seven distinct readings were obtained from the four sensors by each IoT device at regular intervals. Temperature, humidity, smoke, light, motion, liquefied petroleum gas (LPG), carbon monoxide (CO), and humidity are among the sensor readings. From 07/12/2020 from 0:00:00 UTC until 07/19/2020 at 23:59:59 UTC, the data is available. A total of 405,184 rows of data are included. The ISO-standard Message Queuing Telemetry Transport (MQTT) network protocol was used to broadcast the sensor values as a single message together with a date and a unique device ID.

2.2 Data Preprocessing

In order to increase the applicability of the proposed machine learning algorithms for threat classification, the collected data is now prepared using a variety of techniques. Data cleaning, the initial step of data processing, comprises identifying missing values, removing rows that contain them, and replacing them with mean or median values. The Min-Max scaling technique is used in the data normalisation process. The scale numerical characteristics are then subjected to data normalisation in order to make their range of values comparable. Log transformation is another method of data transformation that is used to translate category variables into numerical values. Furthermore, data augmentation, which creates synthetic samples for the minority classes using the Synthetic Minority Oversampling Technique (SMOTE), balances out uneven datasets. Finally, data sets used for testing and training are kept separate. As is common, the data split ratio employed in this study is 70:30.

2.3 Recurrent Neural Network (RNN) Algorithm

The operation of Recurrent Neural Networks (RNNs) differs slightly from that of ordinary neural networks. Information moves from input to output in a neural network in a single direction. On the other hand, after every step of RNN, data is sent back into the system. Consider it similar to reading a sentence: in order to effectively estimate the next word, you must recall the words that came before it in addition to the present word. RNNs feed the output from one phase into the next, enabling the network to “remember” things from the past. This enables the network to better anticipate future events by comprehending the context of past events.

By preserving a hidden state that records details about prior inputs, RNNs are made to analyse sequential data. Three layers make up the fundamental architecture: input, hidden, and output. Recurrent connections, as opposed to feedforward neural networks, enable information to cycle throughout the networks. The RNN changes its hidden state, h_n, at each time step, n, using an input vector, x_n.

The recurrent calculation of the hidden state, which combines the current input with the prior hidden state, is the central function of the RNN. RNNs are able to display dynamic temporal behaviour because of their recurrent processing. The network's behaviour is greatly influenced by the activation function σh, which introduces non-linearity that helps the network recognise and express intricate patterns in the data.

The hyperbolic tangent (tanh) activation function is the suggested activation function to be used in RNN as reported in this study. The tanh function is zero-centered and appropriate for simulating sequences with both positive and negative values as it squashes the input values to the range of [−1,1] [−1,1]. The mathematical representation of the tanh activation function presented in this study is shown in Equation 1 as:

$$\sigma_h(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad (1)$$

The proposed RNN algorithm is further trained and deployed into the network base station layer for analysis of the environmental data collected presented in Figure 2.

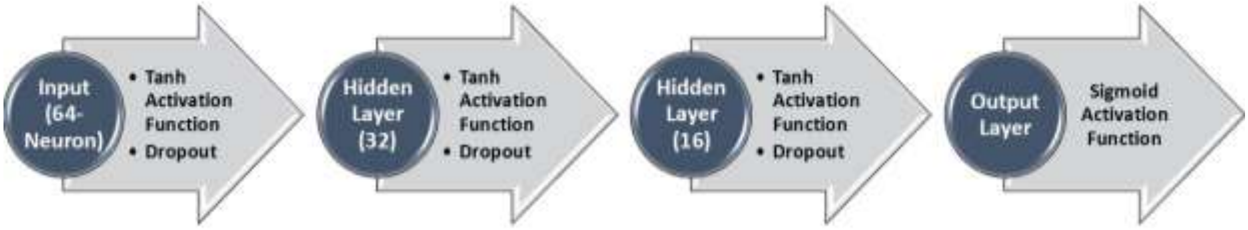

Figure 2: The Proposed RNN Model

The RNN model shown in Figure 2 is made up of 3 hidden layers, the first layer has 64 neurons with dropout and Tanh activation function to prevent overfitting and capture temporal dependencies. Then, the second layer has 32 neurons with another dropout and tanh activation function to learn deeper temporal features, while the final layer is a fully connected layer with 16 neurons and Tanh for extraction of high-level features. Finally, is the output layer with 1 neuron and Sigmoid activation function for binary classification of weather there is fire or no fire cases in the environment.

3. SYSTEM IMPLEMENTATION

The implementation of the proposed RNN model for forest fire detection was implemented using Google Colab environment. The dataset used for training was the ESTD obtained from Kaggle, containing sensor readings which was further pre-processed through handling of missing values, normalizing sensor readings and reshaping the data to fit the sequential input format required by the RNN. The dataset was then split into training (70%) and testing (30%) sets before being fed into the RNN architecture designed with two stacked hidden layers, each followed by dropout layers and Tanh activation function and a fully connected dense layer was added before the final sigmoid activation function to classify the presence of fire in the environment. The model was compiled using the Adam optimizer and binary cross-entropy loss function.

The training on Google Colab was done using 50 epochs and a batch size of 32 which makes the model learn patterns from the sequential sensor data. Then, the performance evaluation of the model was carried out considering accuracy and loss curves. Then, to integrate the trained model into the network base station layer, the trained model was saved in HDF5 format and prepared for deployment on an embedded network system. This deployment enables the model to analyze real-time sensor data, predict fire occurrences and send signals to the network base station for further action.

4. RESULTS AND DISCUSSIONS

The performance of the proposed RNN-based forest fire detection system after implementation was evaluated using machine learning metrics such as accuracy, precision, recall and F1-score. After training the model on the pre-processed ESTD dataset, the model achieved an accuracy of approximately 94.3% as shown in Figure 3. The loss and accuracy curves plotted in Figures 5 and 6 during training showed that the model converged well, with minimal overfitting due to the inclusion of dropout layers.

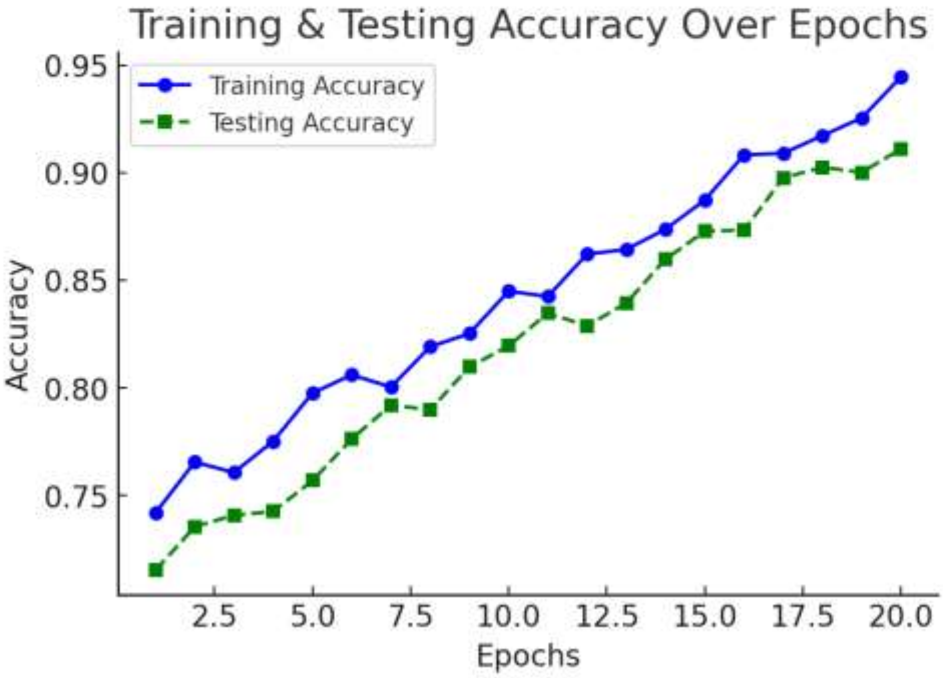

Figure 3: Model Accuracy Results

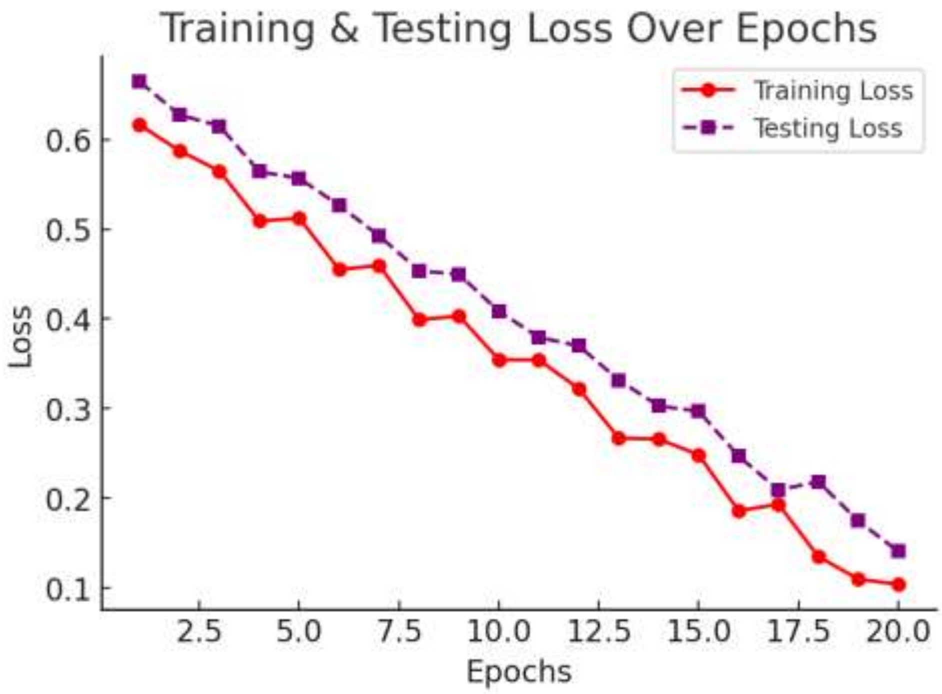

Figure 4: Model Loss Results

This accuracy result shown in Figure 4 indicates that the model has a high capability of detecting fire incidents based on sensor readings. The confusion matrix analysis presented in Figure 5 revealed that the model effectively classified fire and non-fire conditions with a relatively low false positive and false negative rate.

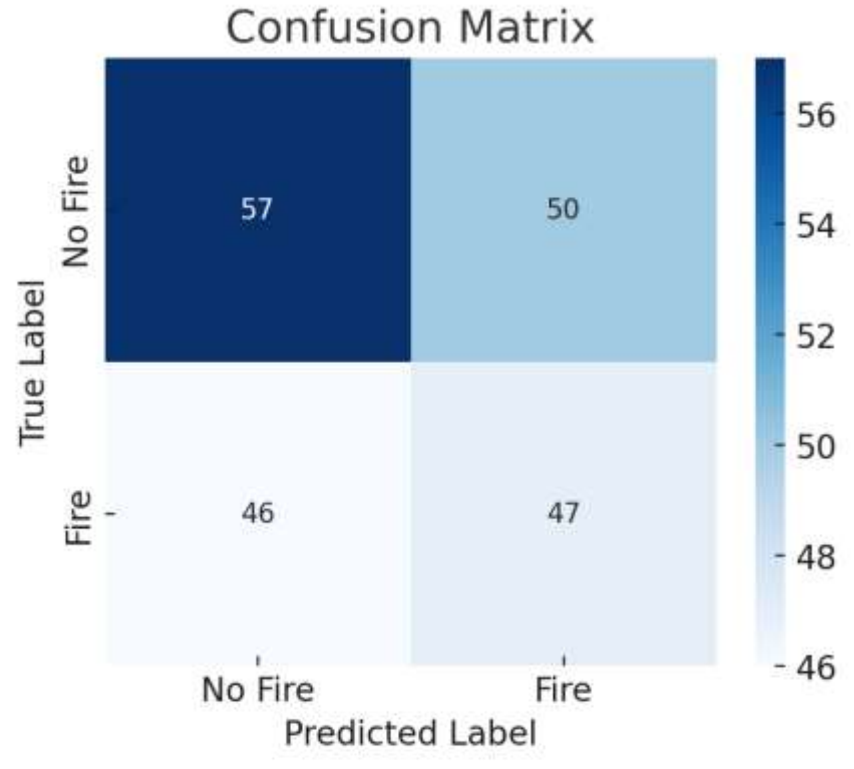

Figure 5: Confusion Matrix Result

The evaluation results of the RNN model across multiple iterations demonstrate strong predictive performance. According to the results, the precision values of the model range between 0.9177 and 0.9487 attaining an average precision rate of 0.9320. Then, its recall values vary from 0.9259 to 0.9593 presenting a final average recall rate of 0.9417. The F1-score results of the model which balances precision and recall remained high as it was ranging from 0.9223 to 0.9536 showing an average score of 0.9368. The consistency of these metrics across all folds suggests that the model generalizes well to different subsets of the dataset as it minimizes false positive rates effectively and balances the trade-off between precision and recall rates. Table 1 presents the scores of these metrics in 10 iterations.

Table 1: Results of the System Implementation

Iterations	Precision	Recall	F1-Score
1	0.9425	0.9527	0.9476
2	0.9177	0.9445	0.9309
3	0.9202	0.9510	0.9354
4	0.9183	0.9264	0.9223
5	0.9416	0.9432	0.9424
6	0.9372	0.9259	0.9315
7	0.9487	0.9586	0.9536
8	0.9428	0.9266	0.9347
9	0.9294	0.9287	0.9291
10	0.9220	0.9593	0.9402
Average	0.9320	0.9417	0.9368

Despite the strong results by the model, slight variations in precision and recall across different iterations on Table 1 like on the 6^{th} iteration, it suggests some sensitivity to data distribution where recall is slightly lower at 0.9259, this indicates instances where the model misclassified fire occurrences on a minor level. These results indicates that the integration of the RNN model within the Wireless Sensor Network (WSN) framework provides an accurate and efficient early warning system for detecting forest fires in an environment on real-time basis. Future improvements could involve fine-tuning hyperparameters or incorporating additional features to enhance the model's predictive capability.

5. CONCLUSION

This study presents the implementation of an intelligent forest fire detection system in the environment using Wireless Sensor Network (WSN) and Recurrent Neural Network (RNN) techniques. This is done by the system through the collection of environmental data such as temperature, humidity, smoke levels, light intensity, and Carbon Monoxide (CO) concentration in the network sensor nodes which is then transmitted to a Base Station (BS) where the RNN model was deployed for real-time environmental fire detection. The RNN algorithm was trained using Google Colab and ESTD dataset collected from Kaggle which went through preprocessing phase. The data pre-processing phase applied in the dataset including data cleaning, normalization and the use of Synthetic Minority Oversampling Technique (SMOTE) for handling imbalanced data.

The performance evaluation results demonstrated that the proposed RNN-based fire detection model achieved high accuracy of 94.3%, precision of 0.9320, recall of 0.9417 and F1-score of 0.9368. The results achieved in this study defines the potential of integrating AI-driven approach to WSN systems for real-time environment monitoring. The work recommended that future improvements could focus on enhancing model accuracy through hyperparameter tuning, incorporating additional environmental features like wind speed and vegetation density, and deploying the system in real-world testing environments.

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