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EARLY FIRE HAZARD PREDICTION FRAMEWORK IN SMART CITIES USING DEEP LEARNING WITH ANTLION OPTIMIZATION ALGORITHM

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ABSTRACT

This study aims to refine the early fire risk prediction model for evaluating the accurate locations of fire using sensor data. Internet of Things (IoT) is integral to smart cities. IoT applications in smart cities include crime predictions, traffic optimization and monitoring of health and environmental conditions. This article reports a study on using Recurrent Neural Network (RNN) with Ant Lion optimization (ALO) framework to enhance and refine the prediction of fire hazards. IoT sensors in smart cities monitor the environmental conditions such as drought, temperature, smoke, flame, relative humidity, fuel moisture and duff moisture. This sensed data is stored in the firebase cloud storage and analyzed in the MATLAB tool. The ensuing enhancement of the proposed model is validated by comparison with conventional prediction models. Our results indicate gains in accuracy and reduction in error rates in fire hazard predictions.

Keywords: *Environment, Fire Hazards, Internet Of Things, Smart City.*

1. INTRODUCTION

The main motive of this work is to enhance the early fire risk prediction model in smart cities with the help of sensed data. With increasing population in smart cities there is corresponding increase in use of the Internet of Things (IoT) devices [1]. IoT systems include self-configurable devices that interact autonomously with network infrastructure. IoT devices have a very low ability to store and process [2] data. These aforementioned limitations of IoT need to be incorporated in fire prediction models. Lack of considerations of IoT limitations can result in inaccurate or complete absence of fire warnings, resulting in loss of the life and property [3]. IoT sensors detect changes in various parameters of the environment. In a conventional alarm system [4], once the parameters (such temperature, smoke, and other environmental conditions) are breached, the IoT systems sound an alarm that will not stop until the environment returns to normal. Alternatively, infrared or ultraviolet detectors [5, 6] are used to detect fire, although they are not suitable for very open and wide regions. Wild forest fires can be detected using satellite remote sensing [7] but such sensing misses out of identifying initial stage of fires. Traditional sensor-based fire detection systems can detect mountains and forest fires at an early stage [8] but they are difficult to implement.

Urbanization has changed the way we live and interact with each [9]. Dense populations face unpredictable hazards [10]. Smart cities are a result of urbanization [11] that demand technology use for traffic, waste management and health monitoring. Such smart cities even deploy alarm systems with blockchain to detect changes to environment parameters and even artificial intelligence systems for economic recovery [12].

Quality of life in a smart city improves through interconnection of tools, automobiles, and infrastructure [13]. Smart building are also a result of effective automation and integration of activities [14, 18]. A crucial requirement in a smart city is to predict fires and take corrective action automatically [15, 19]. Such automation is crucial when a wildfire breaks out as it is usually uncontrolled and destroys property and soil fertility [16, 20]. Timely detection and suppression of wildfires are essential to reduce the extent of the disaster [17].

This paper is divided into six sections: Section II outlines existing literature and the gap, Section III presents the problem statement and the system model, section IV describes the proposed methodology, section V analyzes the proposed platform and results and, finally, section VI concludes with future directions.

1.1 **Research Motivation:**

Existing fire hazard prediction approaches, while functional, often suffer from significant limitations such as inadequate handling of time-series data, poor adaptability to dynamic environmental changes, and suboptimal accuracy in identifying potential fire zones. Traditional machine learning models typically rely on manually selected features and static algorithms that struggle to capture the temporal and nonlinear relationships inherent in sensor data. Additionally, many models do not effectively leverage optimization techniques, resulting in slow convergence and increased error rates. These shortcomings highlight the urgent need for a more intelligent, adaptive, and accurate predictive framework. This research is motivated by the potential of integrating Recurrent Neural Networks (RNNs), known for their strength in sequential data processing, with the Ant Lion Optimization (ALO) algorithm to overcome these limitations and provide a more reliable and efficient early fire hazard prediction system in smart city environments.

2.EXISTING LITERATURE AND GAP

Smart cities incorporate technologies to handle risks – typically through the multilayered framework of Technology-Organization-Environment (TOE) developed by Fahim Ullah, Siddra Qayyum et al. [21]. TOE predicts 56 risks classified into environmental, technological, and smart city based risks. TOE attempts to efficiently manage the predicted risks with the help of integrated IoT systems.

Muh Taufik, Marliana Tri Widyastuti et al. [22] propose an enhanced Peat fire Vulnerability Index (EPFVI) framework to detect environmental as well as ecological degradation. This framework analyzes soil moisture level, rainfall rate and ground water level over the years in order to predict fire risk. This EPFVI framework verified predictions with actual hydrology data. The results demonstrated that the soil hydrological climates properties are influenced the drying and moistening of peats through the capillarity.

Stokkenes, Strand et al. [23] have developed the predictive fire risk indication model. Their experimental setup and validation measurements classify the outdoor environment using a cloud based micro service system. This system stores data and computes the predictions. The geographical locations are validated in terms of measured indoor and outdoor weather prediction system.

Marcel Motta, Pedro Sarmento et al. [24] propose a Machine Learning based GIS framework for urban management. Sensors are used to predict flooding in that GIS framework. Random forest classifier is combined with ML to assess hot spots and improve accuracy of the predictions.

Rosario Fedele, Massimo Merends et al. [25] have developed an IoT based Neural network algorithm predict natural disasters. Their study collects real time data using IoT sensor and transfers it to mobile devices using near field communication technology and shortest path algorithms.

The increased population, building and vehicle density are a fire risk in smart cities. To overcome this kind of challenge, Avazov, K., [7] has proposed a novel convolutional neural network for detecting the fire using You Only Look Once (YOLO) v4 network. The original YOLOv4 method is initialized to find the prediction accuracy of candidate fire regions. Next, the traditional YOLOv4 is improved by the enhancement of the size of the training dataset based on data augmentation methods. The performance of the method is compared with the conventional approaches to test the fire classification results.

Calp, M.H et al [26] have developed Internet of Health Things (IoHT)-based unmanned robot vehicle model by using deep learning methods. These studies have the potential to enhance the prediction and handling of fire.

Our proposed study enhances the work done thus far in fire predictions in smart cities. This study is summarized as follows:

- Place the IoT sensor devices around the smart cities to sense the flame, smoke, temperature, relative humidity (RH), drought code, duff moisture code, fine fuel moisture code.
- Store the sensed data in cloud
- process the data using big data analytics models
- Optimize the recurrent neural network to detect fires hazards at the initial stage
- Update the fire status on mobile phones for immediate action.

Key contribution of the proposed study is summarized as follows,

- Use of IoT sensors in smart cities to collect environmental data such as drought code, temperature, smoke, flame, relative humidity, fuel moisture and duff moisture code.
- Then these sensed data is stored in the cloud storage system and data receptor module is enabled to process the further step with the help of big data analytics.
- Design the Recurrent Neural Network (RNN) with Ant Lion optimization (ALO) framework to predict the fire hazards.
- ALO fitness function is imitated at the hidden layer of the RNN framework for prediction of fire hazard process.
- Develop an enhanced fire hazards prediction process including pre-processing, feature extraction, classification and finally prediction.
- In the classification process fire hazard are classified based on the extracted features; then these predicted cases are sent to the mobile phones.
- Finally, the performances are compared with other conventional techniques in terms of accuracy, precision, recall, f-measure, etc.

2.1 Need of the research

In the context of rapidly urbanizing environments, smart cities demand advanced, real-time systems for mitigating environmental threats, particularly fire hazards that can result in catastrophic losses to life and infrastructure. With the proliferation of IoT-enabled sensors capturing environmental data, there is an urgent requirement for intelligent systems that can analyze these vast datasets to deliver timely and precise fire hazard predictions. Traditional fire prediction models often fall short due to their inability to process non-linear, time-dependent data patterns effectively. Therefore, leveraging deep learning models, especially Recurrent Neural Networks (RNNs), in conjunction with optimization algorithms like Ant Lion Optimization (ALO), is vital to enhance predictive accuracy and responsiveness. This integration aims to provide early warning systems that empower city administrators to take proactive measures in fire prevention and disaster management.

2.2 Problem statement

Despite the availability of sensor data in smart city infrastructures, existing fire hazard prediction systems often suffer from limitations such as low prediction accuracy, high false alarm rates, and inability to adapt to dynamic environmental conditions. Conventional models fail to efficiently handle the complex temporal dependencies present in environmental sensor data, leading to delays and inaccuracies in early fire detection. There is a lack of optimized deep learning frameworks that can seamlessly process this high-dimensional, time-series data to generate reliable early warning signals. Hence, there is a pressing need to develop a robust prediction framework that integrates IoT-based sensing with RNNs and the Ant Lion Optimization algorithm to overcome these challenges and provide timely, precise fire hazard alerts.

2.3 Research gap

While numerous frameworks and models have been proposed for fire risk prediction in smart cities, significant research gaps remain. Existing approaches such as the TOE framework, EPFVI, and GIS-based models primarily focus on environmental data or specific risk types, often lacking real-time adaptability and integration of diverse sensor inputs. Techniques like YOLOv4 and IoHT-based systems have improved detection accuracy but are limited in their predictive capabilities and handling of complex temporal dependencies in dynamic urban environments. Moreover, many models are either region-specific or rely heavily on static datasets, reducing scalability and real-time applicability. This highlights the need for an intelligent, unified framework that leverages deep learning and optimization techniques for accurate, real-time

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fire hazard prediction across varied smart city contexts.

2.4 Research questions

- How can deep learning models like Recurrent Neural Networks (RNN) be effectively utilized to predict fire hazards using time-series data from IoT sensors in smart cities?
- What are the limitations of existing fire prediction frameworks in handling dynamic environmental conditions, and how can these be addressed through intelligent optimization algorithms like Ant Lion Optimization (ALO)?
- To what extent does the integration of IoT sensor data and cloud storage improve the accuracy and responsiveness of early fire hazard detection systems?
- How does the proposed RNN-ALO model compare with traditional methods (e.g., YOLO, GIS, and EPFVI) in terms of prediction accuracy, false positive rate, and real-time applicability?
- What are the computational trade-offs involved in deploying a deep learning and optimization-based fire prediction model in real-world smart city environments, and how can these be minimized?

3.SYSTEM MODEL AND PROBLEM STATEMENT

Smart cities are considered inclusive and use various kinds of technology and information for a better quality of life [13]. Environmental conditions such as pollution, weather, toxic waste, chemicals in consumer products, and radiation affect smart cities [14]. In addition, upcoming cities have many high buildings making it more crucial to address the fire conditions to reduce the deficit of the things and lives of the people. Furthermore, climate changes affected the global ecosystem and individuals, leading to more fire-related tragedies [16]. Fig. 1 shows the system model for IoT-based smart cities is demonstrated in.

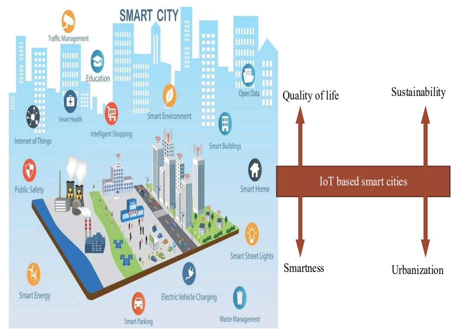

Figure 1: System model for IoT based smart cities

The responses and preparation for this type of hazard are significant because smart cities are affected by various kinds of risks. Furthermore, security issues and the bad performances of the passive and active protection systems are considered the major challenge in smart cities, which cannot perform well based on fire safety standards. These challenges are considered for this new research on smart cities based on early fire hazards.

4.PROPOSED METHODOLOGY

Fig.2 demonstrates a detailed explanation of the proposed RNN-ALO framework. The developed model consists of five steps: IoT device deployment, cloud storage system, data receptor, sensed dataset, and prediction model. The IoT device is critical to perceiving various environmental properties like Flame, smoke, temperature, relative humidity (RH), drought, duff moisture, and good fuel moisture codes. Here, the IoT sensors connect over the cloud storage system. Moreover, the Firebase cloud storage system stores the sensed data.

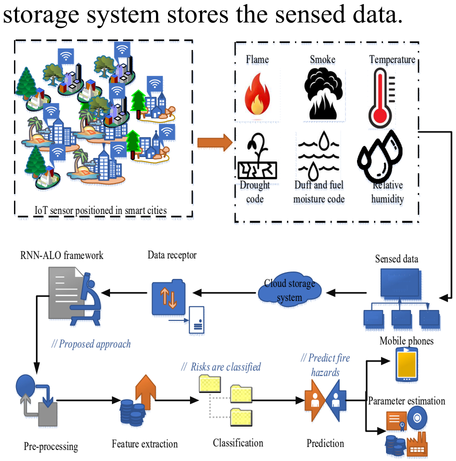

Figure.2: Proposed model

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Then, the data receptor is processed using a heuristic strategy to extract the relevant information. Finally, based on the proposed model can efficiently detect the fire hazard from the sensed data. The paper aims to develop a structural design for predicting fire risks across intelligent cities. Moreover, the developed RNN-ALO model of early fire prediction includes fire prediction using IoT and optimization techniques. Many real-time environmental conditions are collected here, and the fire risk events are validated using the optimization fitness function. Finally, the particular mobile nodes receive an alert signal or warning message.

4.1 SENSOR DEPLOYMENT

The proposed methodology's first part is sensor deployment, meaning IOT devices are positioned in intelligent cities to sense environmental conditions. These sensor devices can collect the ecological parameters in the deployed field area. Here, there are many environmental conditions like drought code, temperature, smoke, flame, relative humidity, fuel moisture, and duff moisture code. Moreover, the sensor devices communicate with the help of a radio frequency link and data to the sink hub. Consequently, the sink hubs gather the sensed information and send it to the Firebase cloud storage system. Here, the cloud storage systems act as the storage platform to store the real-time data and give its assessment for observing and making the finest decision.

4.2 CLOUD STORAGE SYSTEM

Next, the primary phase is a cloud storage system for analyzing the sensed data from the IoT sensors. The environmental parameters come from IoT devices stored on this cloud system for data analyses, visualization, and aggregation. Finally, the sensed information from the smart city is transmitted confidentially to the cloud platform. This tool can directly visualize live stream information and activates an awareness when required.

4.3 WORK FLOW RNN

The developed RNN framework contains number of neuron layers adapted to the optimization parameters. Moreover, the LSTM unit is incorporated into the internal layers of the RNN. Consequently, RNN has three main essential elements: input vector$(x(t))(x(t))$, output vector $(y(t))(y(t))$and vector time (t). Here, the output function is embedded with the nth internal layer at the particular time period$(RNN_n)_t(RNN_n)_t$. Consequently, the LSTM unit generates the component of the output vectors and that are depends upon the dimension of the each layers. LSTM is the most important part of the RNN since it has larger capacity to train the long term outlying area measures. Moreover, it has three major gates such as input, output and forget gates, which is helps to regulate the information flow between the layers. The updated neural network input gate $I(g)$ function is mentioned in eqn. (1),

$$I(g) = \delta\{[w'.I(g)_t] + [r.w'.b] + [p.I(g) * v^{t-1}] + [B.d.I(g)]\} \quad (1)$$

Where, δ is denoted as tangent function, w' denoted as weightage function, r and b is denoted as feed forward bias parameters, v is denoted as classifier rate and B is explored as sensor deployment parameters. Moreover, the gates are merges as error function, gradient descent, LSTM unit, parameter tuning, etc. Initially, the error function is inverted to the input layer that is vital for predicting the all participants in the RNN output. Error function $(E'(f))$ is denoted in following eqn. (2),

$$E'(f) = -\sum_{i=1}^{p}\sum_{j=1}^{q} D_{pq} \log u\,(i)[x(n); w'] \quad (2)$$

Where, D_{pq} is denoted as pth and qth element of the vector functions, probability function is represented as $u(i)$, and weights among the visible and hidden layer is expressed as $x(n)$. After, finishing the error analysis to initiate the weightage function of each neurons to enhance the output. Then to reduce the gradient descent stochastic function is utilized that is mentioned in eqn.(3),

$$\nabla E'(f) = \frac{\partial E'(w')}{\partial (w')} = \left[\frac{\partial E'(w')}{\partial (w_1')}\cdots\cdots\cdots\frac{\partial E'(w')}{\partial (w_n')}\right]^t \quad (3)$$

Using the above eqn.(2) minimum local values are searched as per the gradient descent stochastic function. If the gradient descent stochastic function is negative representation directly it will change the learning rate otherwise learning rate is changes based on the weightage function that is mentioned in eqn. (4),

$$[E'(w')]^t = \frac{1}{||g||} E_n'(w') \quad (4)$$

Where, g is denoted as cross entropy function. Furthermore, the parameters tuning is possible for RNN. Therefore, the optimization parameters are tuned as the RN framework to detect the fire hazards. The softmax layer defines the output layer for the neural networks. The softmax layer allocates decimal probabilities to every class in multiclass classification. Those decimal probabilities have got to add up to 1.

$$Softmax = S(\vec{x})_i = \frac{e^{x_i}}{\Sigma_{j=1}^{k} e^{x_i}} \quad (5)$$

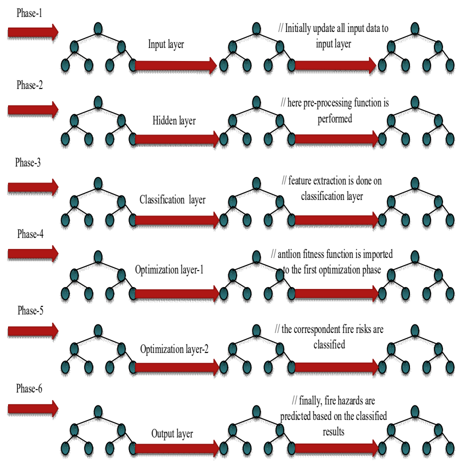

Figure 3: Internal structure of RNN

Moreover, the developed replica has incorporated with six layers such as input layer, hidden layers, classification, two optimization layer and finally output layer. Initially, the collected input data such as flame, smoke, temperature, drought code, fuel moisture code and relative humidity are imported to the input layer to train and training flaws are removed with this layer. Then, pre-processing and feature extraction process is done on hidden layer and classification layer respectively. After that, optimization fitness function is updated in optimization layer-1 and fire risk models are classified in optimization layer-2. Finally, fire hazards locations are predicted and outcomes are reflected in output layer. Fig.3, illustrates the internal structure of RNN.

4.2 PROCESS OF ALO

ALO algorithm is the most common efficient optimization strategy to attain the finest outcomes at the end of the section. Here, ant lions have two main behaviors: hunting and food searching. Moreover, these two behaviors are applied to various optimization issues. The population matrix of the ant lions (al) is mentioned in the following Eqn. (6),

$$M(al) = \begin{pmatrix} al_{11} & . & al_{1n'} \\ . & . & . \\ al_{n1} & . & al_{nn'} \end{pmatrix} \quad (6)$$

Where, n and n' is represented as dimension and populations of the ALO. In general, the ant lions are move randomly so the random walk function x (t) of ant lions are modeled in following eqn. (7),

$$x(t) = \{0, c'[(2r'(t_1) - 1] \ldots\ldots\ldots\ldots c'_n(2r'(t_n) - 1]\} \quad (7)$$

Where, cumulative sum function is denoted as c' that is t step of the random walk movement and iterations are denoted as t. To attain the finest results, the pre-processed data is passed through the sensor event window. A window, includes lot of samples for every climate condition, which are different to require the classification. Then, the normalization functions are incorporated with ant lion position that is mentioned in eqn. (8),

$$x_m^t = \frac{(x_m^t - s_m) \times (p_m^t - q_m^t)}{(r_m - s_m)} + q_m^t \quad (8)$$

Where, maximum and minimum values of the upper and lower boundaries of the ith variable is denotes q_m^t, p_m^t respectively. Moreover, maximum and minimum random walks of the ith variable is denotes s_m, r_m . Then update the maximum and minimum random walks to simulate the ant lion positions that are mentioned in eqn. (9),

$$p_m^t = p^t + al_m^t p_m^t = p^t + al_m^t \quad (9)$$

Then, the classification process is done with the help of optimization parameters that are used to predict the fire hazard risks. The developed RNN-ALO framework is used to classify the fire hazard risks from given collected datasets. Additionally, the feature values are labeled 0's and 1's that means "no fire" and "fire predicted".

Algorithm-1 proposed RNN-ALO framework
Start
Input: fire hazard dataset collected from IoT based smart cities using sensors
Output: early prediction fire risks models
Initialization
$I(g) \Rightarrow$ parameter tuning *// input gate function*
Error function
$E'(f) \Rightarrow$ all vector element functions
weighting function $\Rightarrow$ enhancing the outcomes
gradient descent stochastic function
Case-1 $\Rightarrow$ learning rate changed directly
Csae-2 $\Rightarrow$ learning rate changed based on the weighting function
Fitness updation
Initially update minimum and maximum random walks
$p_m^t = p^t + al_m^t$
$if\,(p_m^t = 0)$
No fire
$if\,(p_m^t = 1)$
Fire predicted

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End if   ***Output:*** finest solution
stop

5 Result and discussion

The developed technique implementation is done in MATLAB framework and compared the performance of the proposed work to prove the efficiency. Moreover, method predicts the fire hazard risk from the collected dataset. Therefore, the proposed testing module is to enhance the classification accuracy of the entire system. For, the implementation Kaggle dataset was collected to predict the fire hazards. Table 1 depicts the simulation parameters.

Table.1 Simulation Parameters

5.1 SIMULATION RESULTS

Sl. no	Parameters	Values
1	Input dimension	9
2	Output dimension	5
3	Learning optimizer	ALO
4	Initial weight	[0,1]
5	Internal layer unit	LSTM unit
6	Initial bias	Nil
7	Error function	Cross entropy

In this section, explains developed RNN-ALO model detection and classification performance using IoT devises. Here, 70% data can be used as training procedure and 30% of data used as testing procedure, which are shown in fig.3. Training accuracy represents the usage of identical datasets for both training and testing performance, whereas test accuracy denotes the trained replica can effectively identifying the independent datasets that were not used in the training process. Moreover, a test accuracy is defined as its capacity to correctly distinguish between fire risks causes. To measure a test accuracy, compute the fraction of true positive and true negative results in all evaluated cases. To analyze the error of the developed model on the training set is a subset of the dataset which are used to train the model initially. Then, the training loss is computed by adding the sum of flaws for each samples collected in the training set. Furthermore, validation loss is a statistic used to evaluate a deep learning strategy performance on the testing set. The testing set is a subset of the dataset, which are put aside to test the proposed model performance. The training and validation loss values are useful because they provide a better understanding of how learning performance changes over time and aid in the diagnosis of any learning issues that may lead to an under fit or overfit model.

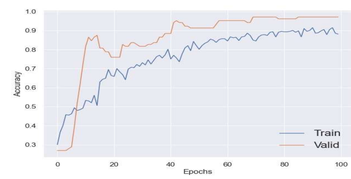

Figure 4: Training and validation accuracy

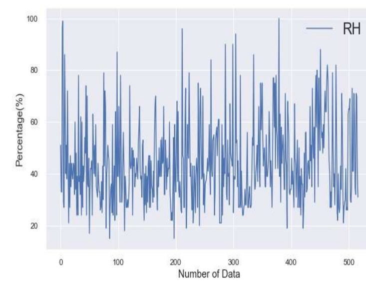

Figure 5: Relative humidity

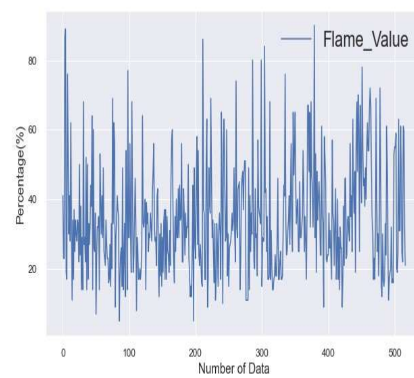

Figure 6: Flame values

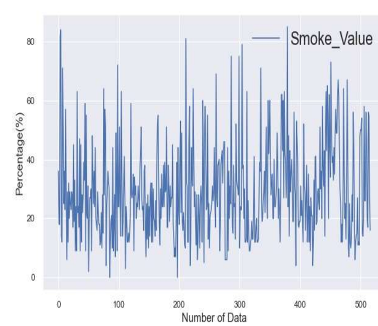

Figure 7: Smoke values

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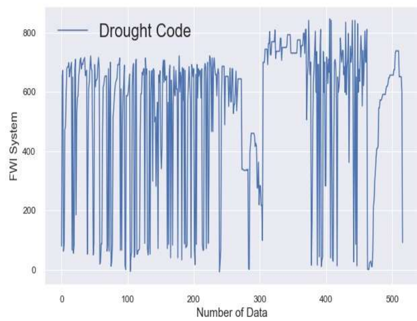

Figure 8: Drought code

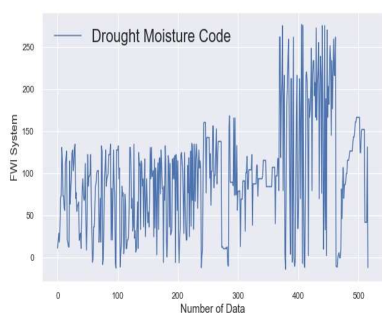

Figure 9: Drought moisture code

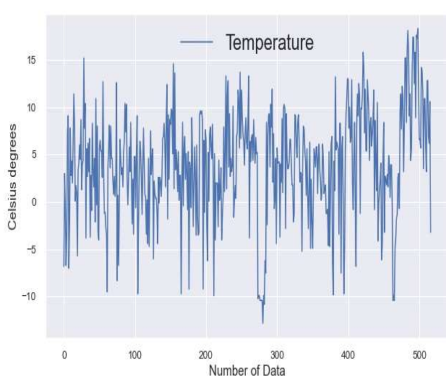

Figure 10: Temperature value

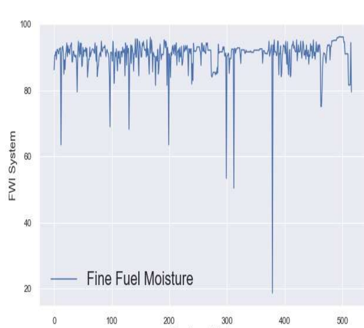

Figure 11: Fine fuel moisture code

Moreover, relative humidity, flame value, smoke value, drought code, drought moisture code, temperature value, and fine fuel moisture code line graphs are illustrated in fig. 4, 5, 6, 7, 8, 9, and 10.

5.2 PERFORMANCE COMPARISON

The implementation of the Proposed RNN-ALO replica is done by MATLAB platform and the simulation results are compared with other techniques in terms of accuracy, true positive rate, false positive rate and error rate. These key metrics are calculated based on the following parameters true positive ($\hat{T}\hat{P}$), true negative ($\hat{T}\hat{N}$), false positive ($\hat{F}\hat{P}$) and false negative ($\hat{F}\hat{N}$), Here, the proposed model is compared with some other existing techniques like YOLO [7], Temperature Early Warning Strategy (TEWS) [27], Optimal Route Selection Model (ORSM) [28].

5.2.1 Accuracy

To enhance the successful rate of the Proposed RNN-ALO model is calculated based on the classification and prediction process. Moreover, the classification and prediction accuracy is measured for extracted features and classified fire risks, that are computed using following eqn.(10),

$$A'_c = \frac{\hat{T}\hat{P}+\hat{T}\hat{N}}{\hat{T}\hat{P}+\hat{T}\hat{N}+\hat{F}\hat{P}+\hat{F}\hat{N}} \quad (10)$$

The proposed RNN-ALO achieved accuracy is compared with other existing techniques such as YOLO, TEWS and ORSM. Moreover, the validation YOLO attained the accuracy rate as 89%, TEWS is has getting 82% of accuracy rate and ORSM attained an accuracy rate as 91% for particular datasets. But, the proposed strategy is has achieved accuracy rate is for 99%. The comparative result in terms of accuracy of the earlier models with the previous methods was displayed in fig.11.

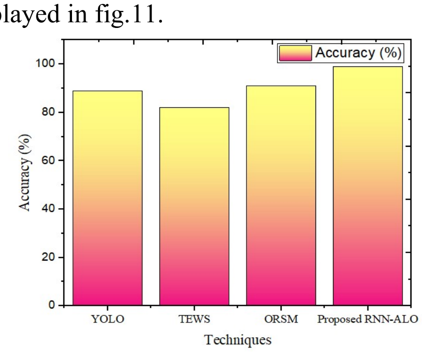

Figure 12: comparison performance of accuracy

5.2.2 TRUE POSITIVE RATE

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It is referred to the accurate positive results occur between the positive samples. However, the proposed RNN-ALO model exceeded all the previous models with a higher true positive measure on the collected dataset. Comparison results are illustrated in fig.12.

$$TPR = \frac{\hat{T}\hat{P}}{\hat{F}\hat{P}+\hat{T}\hat{P}} \quad \textbf{(11)}$$

The proposed RNN-ALO achieved accuracy is compared with other existing techniques such as YOLO, TEWS and ORSM. Moreover, the validation YOLO attained the true positive rate as 56%, TEWS is has getting 78% of true positive rate and ORSM attained a true positive rate as 67% for particular datasets. But, the proposed strategy is has achieved true positive rate is for 99%.

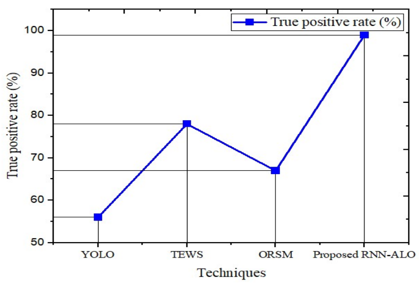

Figure 13: Comparison performance of true positive rate

5.2.3 FALSE POSITIVE RATE

It is defined as the negative results which are incorrectly categorized as positive. Then, the RNN-ALO algorithm demonstrated a better false positive rate. Finally, our proposed RNN-ALO strategy has outperformed all the earlier replicas with a maximum false positive rate in the collected datasets.

$$FPR = \frac{\hat{F}\hat{P}}{\hat{T}\hat{P}+\hat{F}\hat{P}} \quad \textbf{(12)}$$

The proposed RNN-ALO achieved false positive rate is compared with other existing techniques such as YOLO, TEWS and ORSM. Moreover, the validation YOLO attained the false positive rate as 5.89%, TEWS is has getting 8.56% of false positive rate and ORSM attained a false positive rate as 4.67% for particular datasets. But, the proposed strategy has achieved false positive rate is for 1.2%, which are shown in fig.13.

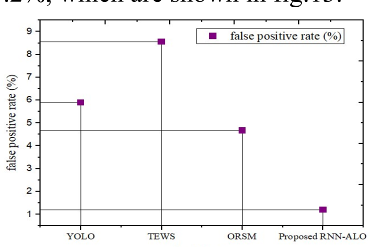

Figure 15: Comparison performance of false positive rate

5.2.4 ERROR RATE

It is referred to the error occurred data in the total number of collected data. The proposed RNN-ALO achieved error rate is compared with other existing techniques such as YOLO, TEWS and ORSM. Moreover, the validation YOLO attained the error rate as 1.56%, TEWS is has getting 0.4% of error rate and ORSM attained an error rate as 0.84% for particular datasets. But, the proposed strategy has achieved error rate is for 0.1%, which are shown in fig.14.

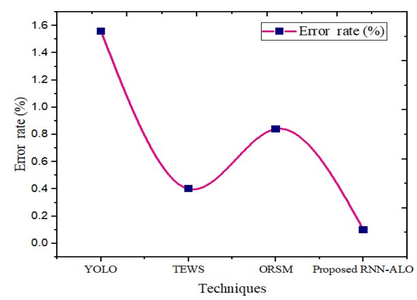

Figure 14: Comparison performance of error rate

5.3 DISCUSSION

The proposed design achieves a very strong interaction module and sensors through the application for exploring, separating, and collecting the detected data for independent direction. The design gives a uniform answer for the recognition of a fire occasion in the beginning phase for utilizing sensors and IoT application. The simulation outcomes for the key metrics are compared with conventional models. The developed RNN-ALO model gives the enhanced performance outperforming the traditional state-of-art strategies in terms of accuracy, true positive rate, false positive rate and error rate which is demonstrated in table.2 and 3.

Table.2 Stat-Of Art-Models

Sl. no	**Author name**	**Techniqu e**	**Merits**	**Demerits**

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1	Fahim Ullah, Siddra Qayyum et al. [21]	Technology-Organization-Environment (TOE) methodology	efficiently manage the predicted risks with the help of integrated smart city TOE layers	The performance was limited due to difficulties in key metrics assessment, evaluating all the parameters under TOE constraint was complex
2	Muh Taufik, Marliana Tri Widyastuti et al. [22]	an enhanced Peat fire Vulnerability Index (EPFVI) framework	soil hydrological climates properties are influenced the drying and moistening of peats through the capillarity	It was suffered due to complexities in the input datasets
3	Stokkenes, Strand et al. [23]	predictive fire risk indication model	efficiently handle the computation time and storage system	Improper manipulation of the differential technique can cause failures
4	Marcel Motta, Pedro Sarmento et al. [24]	Machine Learning based GIS framework	efficiently used for entire smart city provided the observed flood history level	It exhibited high computation time, Convergence with local optimal solutions
5	Rosario Fedele, Massimo merends et al. [25]	IoT based Neural network algorithm	the near field communication technology is applied to provide the various emergency situations	The performance was limited due to improper functioning under specific constraints
6	, Avazov , K., [7]	convolutional neural network	Achieved higher classification accuracy	The system exposed high computation time
7	Calp, M.H et al [26]	Internet of Health Things (IoHT)-based unmanned robot vehicle	Presented a precise design procedure.	Complications in computerized formulation hinder the performance
8	Proposed	RNN-ALO	Higher accuracy and true positive rate, lower false positive rate and lower error rate	-

The proposed RNN-ALO framework has the layers to process the entire works. Initially, the set of collected datasets are initiated to the input layer of the neural networks. Then, pre-processing and feature extraction process performed accordingly. Then, the selected optimization fitness function is updated in the classification layer to classify the results in terms of no fire and fire predicted.

Table.3 Overall Performance

Sl.no	Techniques	Accuracy	TPR	FPR	Error rate
1	YOLO	89	56	5.89	1.56
2	TEWS	82	78	8.56	0.4
3	ORSM	91	67	4.67	0.84
4	Proposed RNN-ALO	99	99	1.2	0.1

The proposed research presents significant advancements by combining Recurrent Neural Networks (RNN) with the Ant Lion Optimization (ALO) algorithm to enhance the accuracy and reliability of early fire hazard prediction in smart cities. This integration enables better handling of time-series sensor data and dynamic environmental conditions, resulting in improved prediction performance over conventional

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models. However, the study also has limitations, including dependency on the availability and accuracy of IoT sensor data, high computational complexity, and limited real-world deployment and testing. Despite these constraints, the research contributes valuable insights into the application of deep learning and bio-inspired optimization for critical disaster prediction systems, paving the way for more intelligent and responsive smart city infrastructure.

6 Conclusion

Fire hazards continue to pose significant threats worldwide, necessitating the development of intelligent and reliable early prediction systems. This research introduces a novel RNN-ALO model that effectively utilizes real-time sensor data deployed across smart cities to predict fire disasters with improved accuracy. Implemented and validated using the MATLAB platform, the proposed model demonstrates substantial improvements over existing approaches, achieving up to 20.73% higher accuracy, 76.79% better TPR, and significant reduction
s in FPR (85.97%) and error rate (93.59%) compared to models like YOLO, TEWS, and ORSM. These results confirm the model's superior performance in early fire hazard detection. However, the research also has limitations, including dependence on the quality and consistency of IoT sensor data, high computational complexity, and limited real-world deployment. Future work will aim to overcome these constraints by integrating hybrid optimization techniques and expanding the range of environmental parameters to further enhance system effectiveness and scalability in diverse smart city environments.

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