Case Study

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Forest fire prediction using IoT and deep learning

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Abstract

Forests are the most important part of the human life as it maintains an environmental balance to get proper rain and sufficient resources accordingly. The major threat raising in forest areas is a fire, in which the forest fire scenario is the most important cause to destroy many trees and animals within a few hours. The technologies such as deep learning, IoT and smart sensors provide a lead to design a smart forest fire prediction scheme to support nature to manage the ecosystem in the proper way. This paper is intended to design a forest fire prediction mechanism. Learning-based forest fire prediction scheme (LBFFPS) based on deep learning has been proposed for the prediction in the timely manner. This approach identifies the forest fire based on the sensor unit associated with the system with respect to the learning logics. A digital camera with 1020-megapixel has adapted for the surveillance. The sensor unit consists of two different and powerful sensors such as smoke identification sensor and the temperature and humidity monitoring sensor. Based on these two sensors the surrounding smoke presence, temperature and the humidity level have been identified and reported using the NodeMCU controller. In this application, internet of things (IoT) is associated, to provide a wireless communication alert ability. It collects and maintain the information regarding the forest provided by the sensor unit to the remote cloud server environment. The NodeMCU microcontroller has an inbuilt WiFi to acquire the internet signals and provides a constant bridge between the sensor unit and the server end for remote data maintenance. The proposed logic is helpful to identify the fire signals and inform the respective person to take appropriate action to prevent the forest fire.

Keywords

Deep learning, Forest fire prediction, Internet of things (IoT), LBFFPS.

1.Introduction

Forests are valuable concerns for human existence as well as societal progress because they help maintain the universe's entire ecosystem stability [1–3]. Unfortunately, forest fire scenarios occur regularly as a result of certain unregulated human activity and erratic environmental circumstances [4, 5]. Such fires are by far the most destructive to environmental assets as well as the human ecology [6–9]. In this situation, forest fire scenarios have significantly increased in regularity as a result of global warming, mortal activity and certain other things [10, 11].

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The identification and surveillance of such forest fire scenarios have become a worldwide problem for communities dedicated to forest fire scenario management. As a consequence of environmental temperature, the chance of igniting a fire rises exponentially. Forest fire scenarios are rising in frequency and it will continue to do so. To assist firefighters on the battlefield, a technique for early identification of forest fire scenarios is provided in this paper. This technique seems to be more exact than other means of communications, including such observation structures as well as surveillance systems. This paper is based on the collection of atmospheric wireless data communication from the forest area and the prediction of forest fire scenario occurrence using deep learning strategy with respect to artificial intelligence logic. The evaluation and comparison of many models produced from deep learning enabled us to demonstrate the viability of an independent as well as legitimate ecological surveillance infrastructure for evolving risk associated with forest fire scenarios.

In this paper a deep learning-based forest fire prediction logic have been applied using internet of things (IoT) and smart sensor unit assisted device called a smart forest monitoring kit (SFMK) for the forest fire prediction. In this SFMK, different smart sensors and devices are gathered to provide a sufficient service to acquire the data from forest environment. These details are forwarded to the cloud server for further processing. In the server end, a deep learning model called learning-based forest fire prediction scheme analysed the incoming data to check the forest fire indications. If any fire indications are identified, immediately that will be alerted to the respective person to take an appropriate action.

The main aim of this research is to provide a sufficient methodology to avoid forest fire accidents, in which it causes a huge destruction to people around the forest as well as the living beings and animals found in the forest region. This research is helpful to identify the forest fires at an earlier stage and report it accordingly to the respective authority to alert them to take appropriate action to preserve the disaster further. Mainly the intention of this research is to save the living creatures and trees present in the forest area from this kind of disaster. This kind of forest fires causes a huge loss in the natural environment and spoil the trees presented into the forest. So that the natural environment balancing is mismatched and even the continuous cause of such things leads to an environmental collapse.

Forest fire prediction systems presently rely heavily on processions, inspection of guard posts and more recently, surveillance systems [1, 2]. While monitoring from guard posts is simple as well as feasible, it does have a number of drawbacks. To begin, this approach necessitates significant technical and logistical resources, and also a highly skilled labour workforce. Furthermore, numerous issues with fire prevention workforce exist, including inattention, leave from duty, a shortage of actual surveillance capability and restricted coverage area [1–8].

Satellite based forest fire surveillance technologies' usable spectrum is also constrained by a number of characteristics, reducing their usefulness in detecting forest fires. For instance, an intelligence gathering system works on a continuous screening period and its overloaded pixel dotted images have a few features. The additional issue is that cloud coverings might obscure photographs throughout the screening phase and quantitative characterization of forest fire parameters in a timely manner is exceedingly hard to perform [3, 4]. Due to these challenges, IoT enabled devices with wireless communication network-based data transmission technology as a monitoring system are needed [5]. It is capable in analysing real associated factors, such as temperature and relative humidity and transmitting the data directly to the remote cloud server monitoring computer. It will be helpful in the organization and analysis of the information gathered. In comparison to conventional data and fundamental sustainable forest information, the technology is capable of making an instant evaluation of a possible fire threat. The gathered information will subsequently be forwarded to the appropriate authority as the foundation for setting regulatory regarding firefighting or rescue operations.

The objectives of this paper are as follows:

1. To develop a framework based on deep learning model for the accurate forest fire prediction scenario and report to avoid disasters in a timely manner.
2. To establish a proper communication and monitoring based on IoT device.
3. To integrate the SFMK for the intellectual monitoring scheme with respect to sensors and camera associated with it.

In this paper an efficient learning-based forest fire prediction scheme (LBFFPS) have been proposed to identify the forest fire. The logical evaluation of such schemes provides a good prediction logic and abilities to monitor the forest-oriented information from anywhere in the globe by using wireless communication medium.

The rest of the paper is organized as follows. Literature review has been discussed in section 2. Section 3 contains the method discussion. Results and discussion have been explored in section 4. Concluding remarks have been pointed to the final conclusion section.

2.Literature review

In this section latest related work has been discussed with the proper elaboration of advantages and limitations.

Lin et al. [12] used the fuzzy prediction algorithm in Jiangsu Province, China, which has a dense population and frequent forest fires. Jiangsu Province is located in the southern region of China. To assess fire danger and quantify the quantitative potential fire risk, a fuzzy inference and large data analysis approach are developed. Fuzzification and output fire rating level are used to transform these factors to triangular fuzzy numbers. The rechargeable wireless sensor network collects continuous 24-hour weather data that can indicate the high accuracy status of the forest environment. This system can detect a high danger of probable forest fires, indicating that there is a need to pay greater attention to forest fire prevention.

In 2019, Zhu et al. [13] described and analysed the machine learning-based forest fire prediction approaches that use wireless sensor networks (WSN) technology and perceptron algorithms to give a reliable and speedy detection of probable forest fires. The sensors were used to collect weather data, which is subsequently sent to a server, where a fire hazard index can be generated. From June to September in the year 2015, they erected a collection of sensors in Nanjing to record weather parameters such as wind speed, temperature, humidity and rainfall, in order to evaluate the efficacy of the perceptron algorithm for forest fire prediction. Forest fire prediction may be implemented in a more convenient method using the perceptron model and Lora technology. The proposed system still has limits due to the minimal data acquired, and it will need to be evaluated for a longer period of time before being deployed in reality.

In 2019, Tehrany et al. [14] provided a comparative case study in the Lao Cai region of Vietnam, which evaluates the usage of the LogitBoost ensemble-based decision tree (LEDT) machine learning algorithm for forest fire susceptibility mapping. In the comparison, support vector machine (SVM), random forest (RF), and kernel logistic regression (KLR) was employed as benchmarks. Based on data from previous forest fire occurrences, a fire inventory database for the selected region was built, and relevant conditioning factors were developed from a variety of sources. Following that, forest fire probability indices were computed using each of the four modelling techniques, and results were compared using the overall accuracy, sensitivity, AUC, specificity, negative predictive value (NPV), positive predictive value (PPV), and, Kappa index. The LEDT model offered the best results, both in terms of training and in terms of results. The LEDT model outperformed the others on both the training and validation datasets, with a prediction accuracy of 92%.

In 2019, Zhang et al. [15] proposed that utilization of convolutional neural network (CNN) to develop a geographic prediction model for forest fire vulnerability. A geographic information system was used to map past forest fire locations in Yunnan Province, China, from 2002 to 2010, as well as a set of 14 forest fire affecting elements. The suggested model's prediction performance was evaluated using a variety of statistical measures, including the receiver operating characteristic curve (ROC), area under curve (AUC) and Wilcoxon signed-rank test. The results showed that the proposed CNN model outperformed the kernel logistic regression, SVM, multilayer perceptron neural network and RF as benchmark classifiers in terms of accuracy of AUC of 0.86.

In 2021, Mohajane et al. [16] used the historical data collected from http://www.eauxetforets.gov.ma/ProtectionForet/Incendies/Pages/Incendies.aspx and used it for preparing the forest fire inventory map. The research area is in the Tanger-T'etouan-Al Hoceima region in northern Morocco, and it includes Fahs-Anjra province and Tanger-Asilah prefecture, with a total area of 1685 km2. For mapping forest fire susceptibility in Morocco's north, they developed five new hybrid machine learning algorithms: frequency ratio-random forest (FR-RF), frequency ratio-classification and regression tree (FR-CART), frequency ratio-logistic regression (FRLR), frequency ratio-multilayer perceptron (FR-MLP), and frequency ratio-support vector machine (FR-SVM). To evaluate the model's effectiveness, the area under the ROC and AUC was calculated. In the forecasting of forest fires, the findings showed that the RF-FR model had the best performance with an AUC of 0.989, followed by AUC of 0.959 in SVM-FR, AUC of 0.858 in MLP-FR, AUC of 0.847 in CART-FR and AUC of 0.809 in LR-FR. Thirteen input variables in a well-studied forest-fire dataset from Portugal's Montesinho Natural Park have been tested [17].

The 517 burn events in that dataset have a very positive skewed total burned area distribution. The two-stage prediction process determines the relative influences of the input factors on burned-area forecasts through informative feature selection. Optimizing with independent objective functions for mean absolute error (MAE) and root mean square error (RMSE) gives more information with which to data mining of each total burned area incident was possible. Beyond regression and correlation-based methods, the proposed method might be easily modified to anticipate and data mine generic agricultural systems. They are dependent on complex interactions between meteorological and environmental variables.

In 2021, Singh et al. [18] collected the data from the Indian Meteorological Department. This data is made up of meteorological data from India's forest regions for the last 15 years. The university of california, irvine (UCI) and Indian Meteorological datasets, respectively, contain information regarding forest fires and meteorological data. The UCI dataset yielded 517 instances of data, with 155 instances of data being used for validation. The parallel SVM algorithm is used to construct a reliable Forest Fire Prediction system. In the prediction procedure, SPARK and PySpark were used to do data segmentation and feature selection. To successfully train the meteorological data and predict the forest fire, a parallel SVM model is constructed. For the forecast of a forest fire, Parallel SVM uses the forecast weather index (FWI) and some weather characteristics. To determine the model's efficiency, the parallel SVM model is tested on data from India and Portugal. In the Portugal data, the parallel SVM model has an RMSE of 63.45 while the SVM approach has an RMSE of 63.5.

In 2021, Baranovskiy et al. [19] used the development of information and computer systems for anticipating the fire safety of Russian railways' infrastructure. It facilitates an important link in the battle against fires in WUI areas. They used the parallel computer technology, a numerical investigation of heat transmission mechanisms in the enclosing framework of a wooden building near the forest fire front. The complexity of the algorithm O (2N2 + 2K) is used to implement the deterministic model of heat transmission in the enclosing structure. The NumPy and Concurrent libraries are used to implement the programme in Python 3.x. The calculations were done at the Sirius University of Science and Technology on a multiprocessor cluster. The acceleration coefficient and calculation results for operating modes 1, 2, 4, 8, 16, 32, 48, and 64 processes were shown. The proposed method can be used to assess the fire safety of Russian railways infrastructure installations.

In 2021, Preeti et al. [20] obtained the data set from Kaggle, which comprises of meteorological data, and then conducted an exploratory analysis, which included pre-processing and transforming categorical data to numerical data in order to make the dataset more understandable. Following the preprocessing procedure, hotspot locations are identified using meteorological data from the data set, and models are used to forecast the likelihood of a fire occurrence and send a notification to the nearest station. The Montesano Natural Park in the European country provided 517 observations and 13 variables for the dataset. By using the RandomizedSearchCV algorithm, they performed RF regression and hyperparameter tuning on several sub-samples of the dataset, it fits to numerous decision trees and provide averaging to increase the predicted accuracy and control over-fitting. Forest fire incidents can be represented based on the analysis of models with all of the relevant meteorological parameters. They compared various models for predicting forest fires, including ANN, Decision Tree, SVM and RF algorithms. The use of RandomizedSearchCV coefficient calculation utilising Hyperparameter tuning yields the best results. It obtained the root mean squared error (RMSR) 0.07, mean absolute error (MAE) 0.03, Mean squared error (MSE) 0.004.

In 2021, Vikram et al. [21] proposed the classification model which is based on a traditional dataset taken from Montesano Natural Park in Portugal during a forest fire. They proposed a strategy for using predictive analytics to detect forest fires early. The forest is separated into different zones using this method. The semi-supervised classification technique is used to anticipate the status of a zone, such as high active (HA), medium active (MA), and low active (LA). Static sensors, mobile sensors, and an Initiator node are all present in each zone. Using the Random trajectory generation (RTG) technique, initiator nodes in the LA and MA zones transmit their mobile nodes (MN) to the closer HA zone for speedy forest fire prediction. This strategy creates the MN movement path by generating intermediary sites between the LA/MA and HA zones. The anchor nodes track the movement of MN using a compressed sensing-based Gradient descent (GD) localization algorithm. This approach lowers MN's energy usage, resulting in a longer network lifetime. The accuracy of MN's path detection is improved by analysing its localization error as it travels towards the HA zone.

In 2021, Zhang et al. [22] created two new datasets for segmentation and classification, respectively, by using on four well known public databases i.e., Cair, Bilkent, Corsican and Foggia. The Corsican fire dataset contains 1135 fire photos recorded in various situations, all of which have been manually segmented as ground truth. Foggia is a video collection that includes 14 fire scenes and 17 non-fire scenes. Normal photos and photographs with fire from a variety of scenarios and diverse fire settings, such as intensity, luminance, environment, size, and many more, are included in the Cair dataset. The Bilkent dataset is a publicly accessible collection of 40 video clips, including 13 fire films, that has been used to assess fire detection frameworks. They created the two datasets from above mentioned available datasets. The first dataset is utilised for segmentation tests, so they chose some fire pictures from all datasets that provide ground truth. In this dataset, 1135 fire photos from the Corsican fire dataset are used, while 5000 images are chosen at random from Foggia's 17 non-fire videos. In general, the 6135 images used for segmentation are separated into 70:30 training and testing sets. The second dataset used a total of 3690 training photos, including 110 fire and 110 non-fire images from the Cair dataset and 455 fire and 1880 non-fire images from the Foggia dataset. By resampling using linear interpolation with a resolution of 224x224 pixels, 1631 input images are randomly selected from 40 Bilkent videos for the testing phase. They adopted method Attention U-Net and SqueezeNet (ATT Squeeze U-Net) is a SqueezeNet-based asymmetric encoder-decoder U-shape architecture that primarily works as a forest fire extractor and discriminator. They initially use a Channel Shuflle operation as a feature communicator in the Fire module of classical SqueezeNet, replacing the classical convolution layer with a depth wise one. The updated SqueezeNet is then used to replace the Attention U-Net encoder, and a similar DeFire module is incorporated into the decoder as well. Finally, they used a portion of the ATT Squeeze U-Net encoder to classify genuine fire. The improved SqueezeNet incorporated Attention U-experimental Net's findings reveal a competitive accuracy of 0.93 and an average prediction time of 0.89.

In 2022, Si et al. [23] used the forest fire statistics, vegetation type, climatic data, and digital evaluation model (DEM) data of the fire occurrence. Forest fire data from Yunnan Province's Forest Fire Prevention Headquarters cover the years 1997 to 2018. The vegetation type data comes from Yunnan Province's National Forest Resources inventory data from 2004 to 2009. The China Meteorological Science Data Sharing Service Network (http://cdc.cms.gov.cn) provides meteorological data. The scientific data center of cold and arid Area provided DEM data with a spatial resolution of 90m. They used the spatial overlay analysis, Kriging interpolation, analysis, and a Logistic regression model to investigate the association between the forest fire occurrence and elevation, vegetation types, and meteorological parameters using a fire dataset from 1997 to 2018 in the Lijiang area. To estimate the likelihood of forest fire occurrence and fire hazard rating in the Lijiang area, an optimum logistic model was chosen. They found that the forest fire occurrence was substantially linked with slope, the daily average temperature and relative humidity, elevation, temperature and aspect. The Logistic model has an average prediction accuracy of 86.9%.

It is clearly indicated from the above literature and analysis that the machine learning and CNN algorithms are capable in the forest fire prediction. But there is the need of a proper alert system in the timely manner to avoid it.

3.Methods

In this paper, a deep learning-based approach called LBFFPS has been proposed. It provides a capability to the proposed approach to monitor the forest region with respect to a smart surveillance device called SFMK. The surveillance kit SFMK consists of several intelligent sensors, camera section and an IoT enabled controller. Based on these specifications the proposed approach can easily identify the forest fire and report it to the respective authority accordingly. The sensors associated with the SMOKE are capable in smoke identification, temperature and humidity monitoring. A high definition 1020-megapixel camera is placed into the SFMK to monitor the forest region and report it accordingly to the server entity without any intervention. All these specifications are illustrated in *Table 1*. *Table 1* classifies fire hazard as a consequence of the forest fire scenario based on weather index [24].

Table 1 Forest fire hazard classification with respect to environmental weather index

Weather Index	Ratio	Category	Hazard
Low indexing	0 to 5	Forest fire surface that is encroaching.	Perhaps the forest fire is self-extinguishing.
Moderate indexing	6 to 10	Forest region fires with a less intensity.	Simple to extinguish with hand instruments.
High indexing	11 to 20A	Forest fire surface that is moderately aggressive.	Pumps with electric motors and pipes are essential.
Very high indexing	21 to 30	Extremely hot forest surface fire.	Complex to Control.
Extreme indexing	31 and above	Extreme fire propagation.	It is vital to take swift and decisive action.

Temperature and Humidity Sensor

In this approach, a powerful and robust temperature and humidity monitoring sensor is utilized, that is called as DHT11. This sensor accumulates the temperature by using the standard DHT11 library and converts the accumulated value from Celsius to Fahrenheit by means of the standard formulation as below (Equation 1):

$$T°_F \leftarrow T°_C \times \left(\frac{9}{2}\right)+32 \quad (1)$$

Where T indicates the temperature, F indicates Fahrenheit and C indicate Celsius. The relative humidity is estimated based on the following formulation as below (Equation 2):

$$_rH \leftarrow \left(\frac{Pw}{Ps}\right) \times 100\% \quad (2)$$

Where $_rH$ indicates relative humidity, P_w indicates the density of water vapor and P_s indicates the density of the saturation level of water vapor.

Gas Sensor

This is a limited expense semi-conductor based MQ2 smoke/gas identification sensor module in associated with analog as well as digital outputs that is extremely simple to operate. Like a gaseous substance sensing element, this component makes use of the MQ2 gas, smoke and flammable gas monitoring sensor. It does not involve any additional features; simply connect the power input to voltage common collector (VCC) and ground pins to ground (GND), in which it is good enough to go. The threshold level for digital and analog output can be simply changed through an on-board resistor. This MQ2 module enables users to simply connect the specified sensor to the respective controller such as NodeMCU, Arduino and so on. Due to the service module sensitivity to gas, it could be used to identify forest fires. Additionally, the MQ2 smoke identification sensor is sensitive to combustible liquids such as propane, petroleum-based fluids and hydrogen.

Learning-based Forest fire prediction scheme (LBFFPS)

In this paper, a deep learning based LBFFPS has been introduced. It is executed on the server end to process the data acquired from smart device SFMK. This learning process trains the machine based on the data acquired from the forest region and tests the real-time information with respect to the trained model. The trained model is created from the real-time data acquired from the SFMK, in which the real data accumulating from the device are undergone into cross-validation with respect to the created model. The data is considered to be problem free means; it will be stored into the remote server end for two purposes such as: (i) maintenance and monitoring from remote end as well as (ii) the processed data is maintained in the remote cloud server end for validating the further testing records. The camera module associated with the device is used to monitor the forest regions in a pictorial way to maintain the forest region without any misuses and accidents occurring. The algorithm of LBFFPS illustrates the specification and process flow of the proposed model.

Algorithm: LBFFPS

Input: Forest weather data and smoke ratio, which is gathered from the SFMK

Output: Fire prediction ratio and accuracy metrics

Step 1: Importing the required libraries to process the learning scheme data.

Step 2: Acquire the input from the smart device SFMK and maintain that into the array variable.

Step 3: Split the received values based on the comma separated value and process accordingly.

Step 4: Define the formulation to estimate the temperature with respect to the Equation 1.

Step 5: Define the formulation to estimate the relative humidity with respect to the Equation 2.

Step 6: Load the trained model for further processing.

Step 7: Cross validate the estimated temperature and humidity values with the trained model values, in which it is acquired from the step 6.

Step 8: Intimate the processed specification of the respective authority by means of storing it into the remote server end.
Step 9: Acquire the video streams from the SFMK and accumulate that into the server end video accumulation unit.
Step 10: The video streams are collected and maintain it into the stream ratio of 1020 pixel rates. Embed the video stream into the server end for maintenance.
Step 11: Acquire the MQ2 sensor readings from the respective array index.
Step 12: Cross validate the acquired MQ2 sensor values with the trained model values to identify whether it exceeds the threshold level or stay in a safe state.
Step 13: Inform the reading ratio to the respective authority once the threshold level exceeds the normal level.
Step 14: Estimate the accuracy levels of prediction and time constraints accordingly.
Step 15: Return the prediction accuracy and metrics to the user end for verification.

Figure 1 illustrates the working block diagram of the SFMK. The block diagram of the monitoring kit shows different controller and sensors. DHT11 is a humidity and temperature sensor. It is capable of sensing the surrounding air. MQ2 sensor is the MQ series gas sensor. It is a highly sensitive gas sensor. It is attached with the IoT interfacing for the proper communication and alert services. It is connected to the remote cloud server. It is enabled with digital camera of 1020 pixels. Based on these sensors the surrounding smoke presence, temperature level and the humidity level have been identified and reported using the NodeMCU controller. In this application, IoT is associated, to provides a wireless communication alert ability. It collects and maintain the information regarding the forest provided by the sensor unit to the remote cloud server environment. The NodeMCU microcontroller has an inbuilt WiFi to acquire the internet signals and provides a constant bridge between the sensor unit and the server end for remote data maintenance.

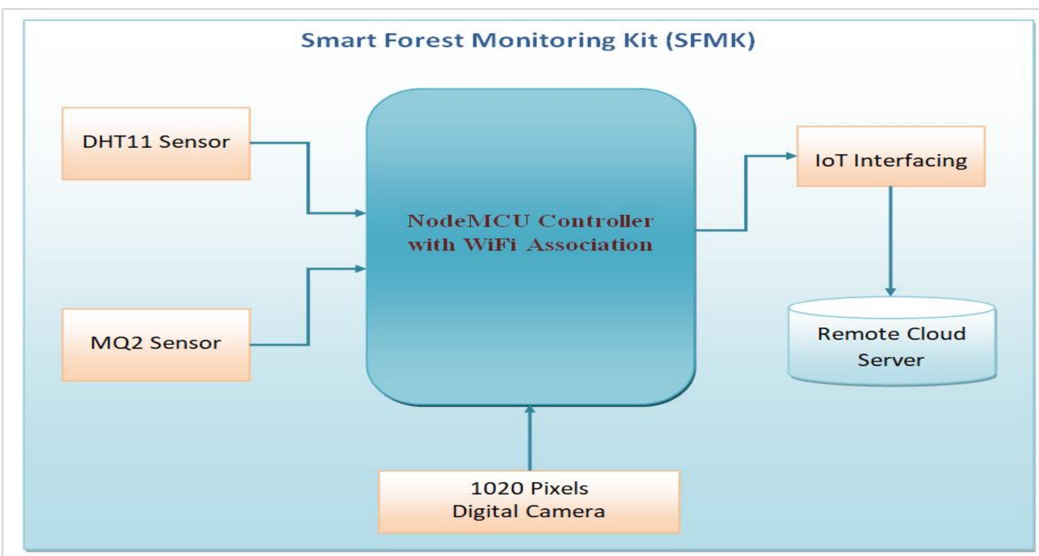

Figure 1 SFMK block diagram

4.Results and discussion

Figure 2 shows the data accumulation efficiency using LBFFPS from the smart device located in the forest region. These ratios are accumulated based on the 10 continuous day surveillance over the real-time forest environment. In which the X-axis indicates the number of days the device is located in the forest region and the Y-axis indicates the data accumulation efficiency. *Figure 3* shows the LBFFPS time consumption scenario to process the data acquired from the forest region by using SFMK. In which the X-axis indicates the number of data accumulated from the forest region and the Y-axis indicates the time required to process the data. The time indications are mentioned in milliseconds over the y-axis. *Figure 4* shows the accuracy comparison based on SVM and LBFFPS. *Figure 5* shows the accuracy comparison based on RF and LBFFPS. The comparison clearly indicates the effectiveness of our approach in comparison to the SVM and RF.

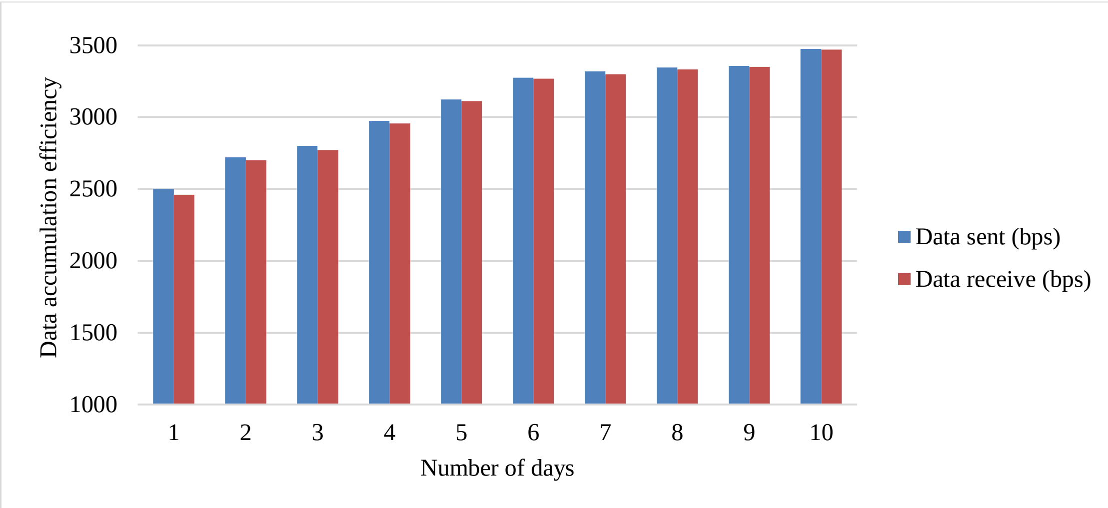

Figure 2 Data accumulation efficiency based on the sent and received cases

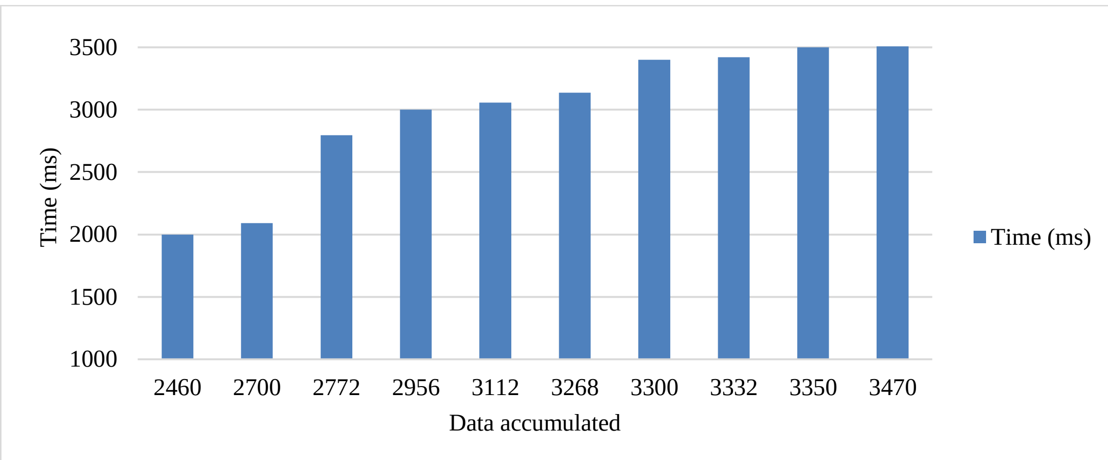

Figure 3 Time consumption ratio based on data accumulated

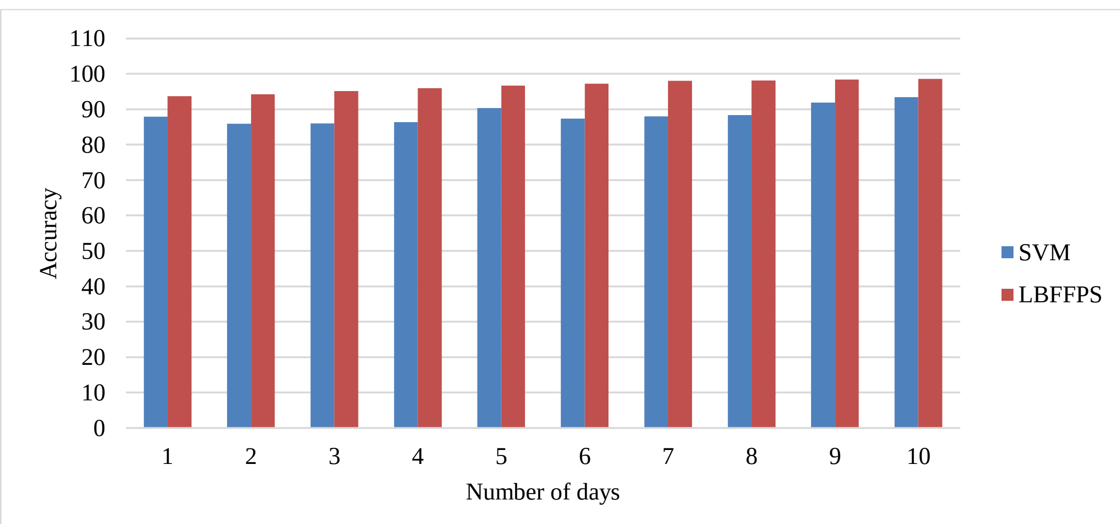

Figure 4 Accuracy comparison based on SVM and LBFFPS

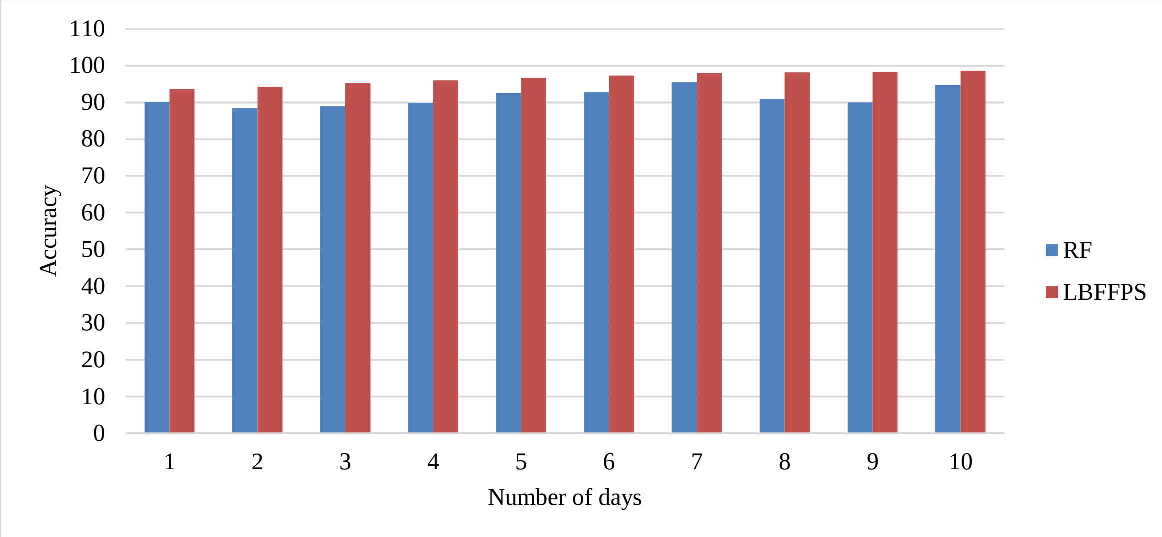

Figure 5 Accuracy comparison based on RF and LBFFPS

Limitations

The proposed methodology is designed based on the deep learning strategy as well as the sensor unit consists of two sensors such as DHT11 and the MQ2 smoke identification sensor. This DHT11 sensor identifies the temperature and humidity level in the correct manner, but over the forest region the temperature and climate constraints are unpredictable as well as the conditions may change within a period of instance. So that a motorized robot-like moving object is required to monitor the forest region in intense manner and report accordingly to the authorities without any delay. These kinds of smart enhancements can add the boosted evaluation to the methodology defined over this paper as well as the proposed methodology need to be refined according to the time constraint to prevent the forest region in good condition. The other limitation is the real time environment. This experimentation was performed with the small sample. So, it should be validated on the large-scale forest with longer time with the performance possibilities. Powerful internet facility is also important in this research.

A complete list of abbreviations is shown in *Appendix I.*

4.Conclusion

This paper establishes and develops a wireless communication model using an IoT enabled network with intelligent sensors. It is capable of measuring forest region data in real-time with global area coverage options. This level of responsiveness is achieved by attaching a simultaneous elevated data capturing module with powerful internet connectivity using weather monitoring sensors such as DHT11 and MQ2. The proposed LBFFPS mechanism is capable of gathering the real-time data acquired from the forest region by using the number of sensors associated with the smart device called SFMK. Additionally, it doesn't require more computing capabilities than a solitary wireless sensor network to form a real-time adaptive network. The concentration on a small number of measures in conjunction with carbon monoxide monitoring implies that the proposed solution is less expensive, real-time functional and effective.

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None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Authors contribution statement

J Ananthi: Conceptualization, methodology, data curation, formal analysis, investigation, validation, writing-original draft preparation. **N Sengottaiyan**: Conceptualization, methodology, data curation, formal analysis, investigation, visualization, writing- original draft preparation, writing-review and editing. **S Anbukaruppusamy**: Conceptualization, methodology, data curation, formal analysis, investigation, writing- original draft preparation, writing- review and editing. **Kamal Upreti**: Validation, supervision and project administration. **Animesh Kumar Dubey**: Validation, supervision and project administration.

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Appendix I

S. No.	Abbreviation	Description
1	AUC	Area Under Curve
2	CNN	Convolutional Neural Network
3	DEM	Digital Evaluation Model
4	FR-CART	Frequency Ratio-Classification Regression Tree
5	FR-RF	Frequency Ratio-Random Forest
6	FRLR	Frequency Ratio-Logistic Regression
7	FR-MLP	Frequency Ratio-Multilayer Perceptron
8	FR-SVM	Frequency Ratio-Support Vector Machine
9	FWI	Forecast Weather Index
10	GD	Gradient Descent
11	GND	Ground Pins to Ground
12	HA	High Active
13	IoT	Internet of Things
14	KLR	Kernel Logistic Regression
15	LA	Low Active
16	LBFFPS	Learning-Based Forest Fire Prediction Scheme
17	LEDT	LogitBoost Ensemble-Based Decision Tree
18	MA	Medium Active
19	MAE	Mean Absolute Error
20	MN	Mobile Nodes
21	NPV	Negative Predictive Value
22	PPV	Positive Predictive Value
23	RF	random forest
24	RMSE	Root Mean Square Error
25	ROC	Receiver Operating Characteristic Curve
26	RTG	Random Trajectory Generation
27	SFMK	Smart Forest Monitoring Kit
28	SVM	Support Vector Machine
29	UCI	University of California, Irvine
30	VCC	Voltage Common Collector
31	WSN	Wireless Sensor Networks