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IOT BASED AUTOMATIC FOREST FIRE DETECTION BASED ON MACHINE LEARNING APPROACH

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Abstract

There are many applications for monitoring the environment thanks to the development of wireless sensor networks and the Internet of Things. As a possible use case for WSNs and the Internet of Things, we investigated the issue of monitoring and detecting forest fires in this paper. The current environmental damage is mostly caused by forest fires. The current forest fire monitoring system falls short in its ability to continuously provide real-time monitoring for every location within a target region and to facilitate early danger identification. Forest fires pose a significant hazard to the ecosystem as a whole, contributing to both global warming and ozone layer loss. The potential answer to decrease the cause or the danger of a fire occurrence by up to 95% is early detection. There are several strategies that may be used to keep woodlands fire-free. The technologies that may be helpful for the early identification of forest fires include satellite systems and unmanned aerial vehicles. Although these systems are capable of covering any geographical area, they are unable to provide real-time information on the full region of interest. Additionally, satellite-based and UAV-based systems are only suitable for monitoring and battling fires. Therefore, it is very vital to make accurate predictions of forest fires at an early stage.

Keywords: Forest, Fire, Internet of Things, Detection, Wireless Sensor Network and Actuator.

1. Introduction

An overview of the worldwide context for forest fires is provided in this section. Studying forest fires is crucial to understanding their causes and establishing the need for further research. The most uncontrolled occurrence that seriously disturbs the whole ecosystem is a forest fire, which must be dealt with by using WSN technology. The motivation for this research's endeavour is to

stop forest fires, and the following justification serves as that motivation. Because of these and other issues, human civilization severely degrades biological variety by negatively affecting biological resources. For the preservation of biological variety, it is crucial to plan forest management using effective instruments. India is a nation with a diverse array of plants and animals [1]. It has been a worry that the destruction of forests brought on by forest fires and other activities impacts animals and threatens their habitat. In order to guarantee the nation's biological and environmental security, a law (the Wildlife Protection Act, 1972) for the protection of wildlife, animals, birds, plants, and items related to wildlife has been established. Article 8 of the CBD addresses the creation and management of protected areas with a focus on resource conservation and ecological restoration (Convention on biological diversity). The value and importance of a nation's protected areas for the preservation of its natural and cultural riches cannot be overstated. Protected places that are well-maintained provide a variety of chances and advantages in terms of ecological, educational, economic, and social aspects. However, these protected areas in a nation are vulnerable to a number of dangers [2]. The most frequent risk in a forest is wildfire, which drastically disrupts and obliterates the environment and fauna. Every year, there are more wildfires on the planet, which poses a serious danger to the overall biodiversity. The phrases "fire risk" and "fire hazard" have been associated with forest fire control since the dawn of science. These two names have been used in several different ways, with numerous distinct meanings. The right interpretation of terminology used in fire management, such as fire hazard, danger, risk, susceptibility, etc., is crucial to avoid misunderstanding their intended meanings. The definition of fire risk is the sum of the probabilities of a fire occurring and the effects of a fire danger that has been recognised. It is used to calculate the damage and loss caused by a fire activity [3]. The likelihood of hazardous fire outcomes and anticipated loss for estimating damage in terms of human and natural property loss are determined by the concept of fire risk. For the use of a fire monitoring system, wireless sensor networks have unique characteristics that provide a number of benefits and several obstacles. Before developing a system for leveraging WSNs to detect fire events early, factors including restricted power, weak sensor nodes, and hostile environmental conditions must be taken into account. This section provides information about sensor nodes, different uses, and their deployment for locating forest fires and gathering data. Recent developments in wireless technology have drawn interest in several real-time application domains. Numerous wireless communication models have been created to support the real-time environment from various angles, such as data transmission, data availability, network security, and so forth [4]. The introduction of wireless sensor networks as a new kind of networking module resulted from the integration of integrated circuits with cutting-edge technology. The manufacturing of sensor devices is in line with communication technologies, ensuring quick and reliable information transmission modules. From the perspective of computational costs, the smaller the devices are, the lower the costs. These characteristics have made wireless sensor networks quite popular with both academics and industry. It facilitates a variety of applications and difficulties for the researchers. The hardware is also improving at the same time, which facilitates the implementation of sensor networks in a real-time context [5]. The potential of sensor networks in several types of

network modelling, such as routing, data analytics, task scheduling, network localisation, key management, and cryptography, has been extensively researched. These types of sensor network applications need the creation of low-cost, low-power, multifunctionality-supporting, and efficient communication capabilities. It has inspired the creation of a team-based workplace using various sensor networks. According to the needs of the application, a sensor network is a kind of ad-hoc network that includes a substantial number of sensor nodes. These sensor nodes have the capacity to sense the surrounding environment by using factors like temperature, humidity, light changes, and more [6]. The deployed sensor node has the ability to interpret data and perform computations despite perceiving its surroundings. It was observed that the nodes' sensing capabilities changed depending on the wireless communication connections' range. Since the sensors are powered by batteries, a long lifetime is anticipated; yet, in the hostile environment, it acts invisibly. The sensor nodes are reusable and provide mass deployment for monitoring an area at a minimal cost. Because it adheres to these qualities, it is appropriate for use in large-scale applications. As was previously said, a sensor network is made up of a number of sensor nodes that are very helpful to put within the forest. The modulation or pre-estimation of the sensor nodes' positions has not been done. At the interior of the forest, the sensor units are dispersed randomly. In order to protect the environment, Wireless Sensor Networks (WSNs) are used to identify forest fires early on.

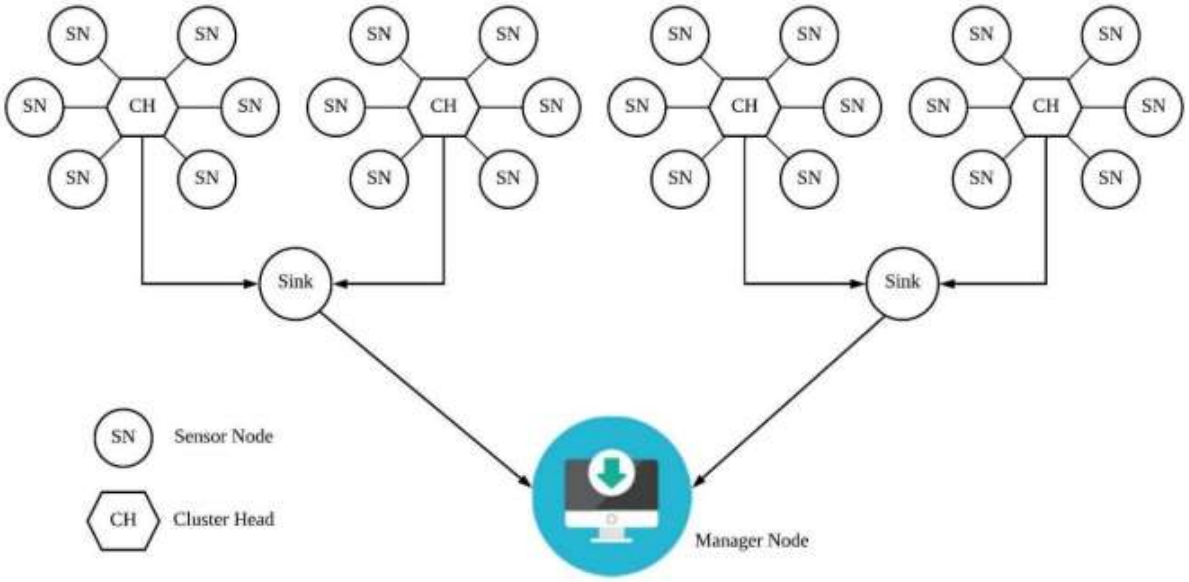

Figure.1: Architecture of the WSNs deployment in forest environment

The deployment architecture of WSNs in a forest setting is shown in Figure 1. It shows the hierarchical architecture of a wireless sensor network, where all sensor nodes are connected at the lowest level. By using the data from the sensor nodes in their individual neighbourhoods, the sensor nodes build clusters and choose a cluster head (CH). The selection of the cluster head is influenced by crucial factors such limited energy resources, the quantity of nearby nodes, and proximity to the base station [7]. The field data is gathered by each sensor node at the lowest level, and it is then sent to the appropriate cluster head. Information that has been detected is sent to the

sink node via the cluster heads. Every level of the hierarchy repeats the same data collecting procedure. It is the coordination node's responsibility to compile the necessary data and send it to the management node or base station for analysis. The implementation of sensor networks is made more difficult by the scarce energy resources and hostile forest environment [8]. Deploying sensor networks is primarily responsible for monitoring the environment for any unusual occurrences of events. In the context of forest applications, it is used to monitor the forest's terrain for any unforeseen environmental catastrophes like fires. By gathering the temperature or humidity of the region in the forest, it provides information to the relevant parties. In order to gather data on the woods, the sensor node uses wireless networks to connect with the forest fields [9]. Any forest area's acquired data is sent in many hops to the sink node. The gateway connects each sensor node to the other networks. The deployed sensor nodes in the forest are outfitted with wireless communication devices since they are unsure of where they will be placed. Due of the environmental flaws prevalent in the forest, there is a great likelihood that the nodes would malfunction.

2. Literature Review

In this specific area, "How to Protect our Environment from Degradation," much study is being conducted. Forest and rural area fires are the primary cause of the poor environment. There are several factors that contribute to forest fires, and for the longest time, the only way we can see the tragic events as they unfold is by reading about them in newspapers, magazines, or online. The goal of this body of research is to examine numerous methods for detecting forest fires in order to determine which method is most effective for use in real-time applications. Several research databases are retrieved for the current study due to the diversity of research publications in the field of forest fire detection [10]. In this research, we looked into six distinct databases to investigate the most current developments in the use of fire detection. This chapter provides a short overview of previous work in the field of forest fire detection that served as our inspiration for creating a reliable early fire detection system as well as a solution to the false alarm and localization problems. The efficacy of different techniques in terms of accurate and early detection of forest fires is evaluated after a thorough literature review that outlines the significance of forest fire detection systems. This chapter goes into depth about the initiatives done by several researchers in this application for monitoring, mapping burned areas, and early fire detection. Some research gaps have been found in this chapter based on the performed literature assessment, which has led to the beginning of the thesis research work's aim framing[11]. At the conclusion of this chapter, the contributions of the planned work in this thesis are also covered. Since the late 1990s, there have been several satellite systems that may be used to provide data and other operational capabilities for the application of forest fires. In the literature, there were several efforts by different researchers to monitor forest fires using satellite systems. Fire detection, monitoring, and area evaluation may all be done using satellite-based systems. The benefit of employing a satellite-based system is that it can cover any large region. The majority of satellite-based systems are used for tracking forest fire activity and assessing burned areas [12]. There are several satellite-based methods that may be used to detect fires via remote sensing. These strategies are described

in the literature and in this chapter's section. A remote sensing-based strategy to monitoring and predicting forest fire threat is presented in [13]. Monitoring forest fires with remote sensing is a way to describe the present situation. Four phases make up the remote sensing-based monitoring process: the acquisition of relevant data, calculation of resultant variables that correspond to danger situations, establishment of relationships between the resulting variables and risk indicators, and creation of risk maps. The variables collected from remote sensing include the vegetation state, meteorological factors, and surface conditions. Their study focuses on the drawbacks of systems that use remote sensing to track environmental threats and anticipate risk factors. The primary purpose of the remote sensing-based approaches is to calculate the indications of fire occurrence and compare the results with actual fire. Although the system has certain limits, there are numerous ways to improve it and get it to be dependable and acceptable. [8] reports another method for detecting fire via distant sensing that addresses the problems of accurate detection and lengthy calculation. Their detection system gathers pictures from sophisticated, extremely high-resolution radiometers for processing (AVHRR). The design has a number of benefits, including totally autonomous operation, consistently high data quality, and cost effectiveness, but one drawback is that the outcomes are not immediate. The technology exhibits false detection and has not been evaluated for consequences in real time. Forest fire detection methods based on IR cameras and image processing are helpful for confirming fire incidents. This section examines image processing-based fire detection systems that address the need for fire event confirmation in order to decrease false alarms. It has been noted that several researchers have made outstanding efforts to design effective systems for fire confirmation. A multi-feature analysis of smoke particles for the confirmation of forest fire is described in [11]. A method for image processing is suggested for video signal smoke detection. According to their system, the use of video in smoke detection has a number of advantages over earlier methods, including a wide coverage area and a quick reaction time. They have employed three distinct aspects in their study on the decrease of false alarms. To locate or describe the smoke area known as a candidate, colour is first filtered in YUV colour space. Next, spatial and temporal information are retrieved from the smoke candidates using spatio-temporal analysis and dynamic texture analysis, which are then submitted to SVM for classification. In compared to other strategies already in use, investigations based on their study demonstrate that their methodology has a high detection rate and speedy processing. An intelligent method for monitoring forest fires is provided in [12]. They have put up a system architecture for an image-processing-based platform. They want to create a system that can automatically detect fires. An intelligent system called iForestfire is based on the monitoring of video cameras that can be managed remotely and the integration of metrological stations with geolocational information systems. This data is originally evaluated in real time to identify fire. The technology is very accurate and compatible with a variety of tools, including Sony and Samsung cameras.

In [13], an algorithm for video analysis was created using VS2010 and Open CV2.1 to identify flame and smoke. The authors employ backdrop modelling to extract the area, followed by mixed colour space features to identify the flame, then threshold segmentation to detect smoke. The

outcome demonstrates the suggested system's accuracy in terms of precise detection. In [14], a real-time detection method that uses spatiotemporal analysis of video was presented. There are various phases in the suggested architecture's technique. Background removal is done in the first step, and then fire categorization using colour analysis is done. Following the computation of a few characteristics whenever fire is detected, the classification procedure then occurs. The scientists applied innovative characteristics to distinguish between actual fire pixels and fire-like pixels; as a consequence, there are fewer detection errors and the system performs better.

Using spatiotemporal modelling and texture analysis, [15] suggested an automated fire detection method based on video analysis. Filtering out the coloured, non-fire moving zones is the first stage. Because of its effectiveness and quickness, background removal comes first in the adaptive median algorithm's process of extracting features. The colour analysis is then carried out using the RGB colour distribution in the next phase. For each identified fire candidate, the six separate characteristics are calculated. The fire colour probability is the first feature to be identified, and then the spatial wavelet energy analysis, the spatio-temporal energy, and the last three characteristics to be calculated. Finally, categorization is completed in order to make decisions. The obtained findings show how well the technique performs for precise detection.

A wildfire colour segmentation system was given in [16]. For fire colour segmentation, they examined eleven methods. The YCbCr model is used in the suggested approach to minimise the impacts of light. According to the experimental findings, segmentation can detect fire in the daytime without smoke. [17] has developed an edge detection method for the image-processing-based identification of flame edges. They have provided a computational technique that can clearly and continuously describe flame and fire edges. The histogram is first normalised to modify the grey scale, and after that, background noise is eliminated to smooth the picture. After background noise has been eliminated, the basic edges are determined using a sobel operator, and then the higher and lower threshold values are adjusted. For the purpose of distinguishing between a preparatory picture with edges and the actual image, they built a least mean square algorithm, and in the final phase, the undesirable edges were deleted. The results of the experiment demonstrate how well-suited and reliable their algorithm is at identifying fire flames of various colours. The main benefit of their approach is that the fire edges are sensed clearly and continuously. A CCD camera-based fire detection system has been developed in [18]. The created method uses statistical parameters like standard deviation and mean values for the verification of fire pixels to forecast the fire pixels from grayscale frames of films. Real-time images are utilised in conjunction with the developed system's smoke detecting capabilities to validate fire and non-fire incidents. A system that employs the YUV space model for fire detection is reported in [19]. While the chrominance U, V are computerised for the categorization of fire and non-fire pixels, the design computes the luminance Y for the declaration of candidate area. Additionally, the study they propose computes motion vectors to understand the behaviour. The technology reduces the false alarm rate, according to the published experimental findings, although there are no tests for performance validation. The background noise in the system causes a significant number of false alerts. This section explores the use of machine learning and deep learning to build fire detection

systems that can satisfy the demands of high computing speed, energy efficiency, and accuracy. It has been discovered that several researchers have made outstanding attempts to construct effective fire detection systems utilising ML and DL approaches. Many research efforts have gone into developing fire confirmation methods, and the work that has been done in this area is detailed in the part that follows. Author shows a support vector machine fire detection. Although the technique is effective in terms of precise detection, calculation time is lengthy. A crucial factor in fire event modelling is the fire weather index. The FWI is a complete system that has been supported throughout North America for many years. A data aggregation strategy is given and put to the test for a wildfire detection application using the FWI system. Their data aggregation method's key benefit is that it only sends the data that the application is interested in. The experiment's findings demonstrate that the system provides trustworthy coverage. A fire event prediction algorithm based on ANN was created in [20]. The technology uses artificial neural networks to enable automated decision-making. Data is first gathered via sensors (Micaz mote), then passed to an ANN that has previously been trained, which then determines whether or not there is a fire. The results highlight the value of their architecture for detecting fire together with the understanding of fire development direction. Without any human oversight, the technology continually monitors the forest fire. The same model's potential for future development includes being expanded to precisely locate the position of the firing point. [21] suggested a cellular automata-based approach for simulating the incidence of forest fires and their propagation throughout a zone. The authors have enhanced the forest fire model and gone through computer algorithms in their study. They have integrated dynamic updating of tree clusters and are working on a breadth-first strategy, which reduces time. The outcome demonstrates how practical and very successful the design is. Their paper is realistically applicable to the majority of fire forecast and management applications. [8] discusses the significance of statistical data modelling for precise fire detection. The model was created with both indoor and outdoor contexts in mind. The design tackles the energy and delay problems and has been tested in a variety of environmental settings. In sensor networks, energy consumption is a crucial problem. A network's optimization problem lowers performance and raises energy use. For the purpose of optimising, a harmony search method is helpful in lowering intra-cluster distance [9]. The experimental finding demonstrates that employing HSACP increases network longevity compared to LEACH-C and FCMCP. [22] addresses the optimization problem and in WSNs during routing. The authors used the swarm intelligence method to create a routing algorithm for WSNs. An artificial bee colony algorithm is used to regularly gather environmental data. Ant colony optimization technique is used to extend network longevity. They combined the two algorithms, ABC and ACO, in their study and created the ABCACO method to address an optimization and finite issue in WSN. Three key elements make up their algorithm. The outcome demonstrates how effective their method is at watching for and identifying fire. When compared to Leache, their approach improves both stability and output. Using VS2010 and Open CV2.1, n [13] have created an algorithm for video analysis that recognises flame and smoke. The authors employ backdrop modelling to extract the area, followed by mixed colour space features to identify the flame, then threshold segmentation to detect smoke.

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3. Proposed Forest Fire Detection System

Our research tries to provide a paradigm that takes into account three fundamental objectives of forest fire detection. 1) Constant environmental monitoring at all times; 2) Reduced power usage; 3) Adaptability to harsh conditions; and 4) Early fire event detection. Early forest fire detection is important for environmental preservation. The use of image processing or other approaches to anticipate forest fires is well-documented in the literature. Although several studies have used satellite systems for fire monitoring, the adoption of these approaches is currently unfavourable in part due to high costs, poor resolution, and lengthy procedures. As far as early feasible detection of the forest fire is concerned, real-time execution of these technologies is not conceivable. IR cameras and Unmanned Aerial Vehicles (UAVs) [8,9] were used for the detection procedure in the deep analysis. However, line of sight vision is initiated by the IR cameras, which degrades the collection of fire events that are not located in the LOS region [23,24]. The usage of UAVs is rapidly increasing, as well [25]. As a result, the process of sensor measurement is essential to the process of finding forest fires. As a result, this part shows how to install sensor nodes effectively to gather sensor data. In WSNs, there are typically two kinds of sensor nodes: mobile and stationary nodes. With regard to sensor node size, proper sensor node placement inside the forest coverage area becomes crucial. With the aid of sink nodes, the deployed sensor module collects data and then exchanges it with the base station. The selected approach for the forest fire detection procedure is shown in Figure.2 below.

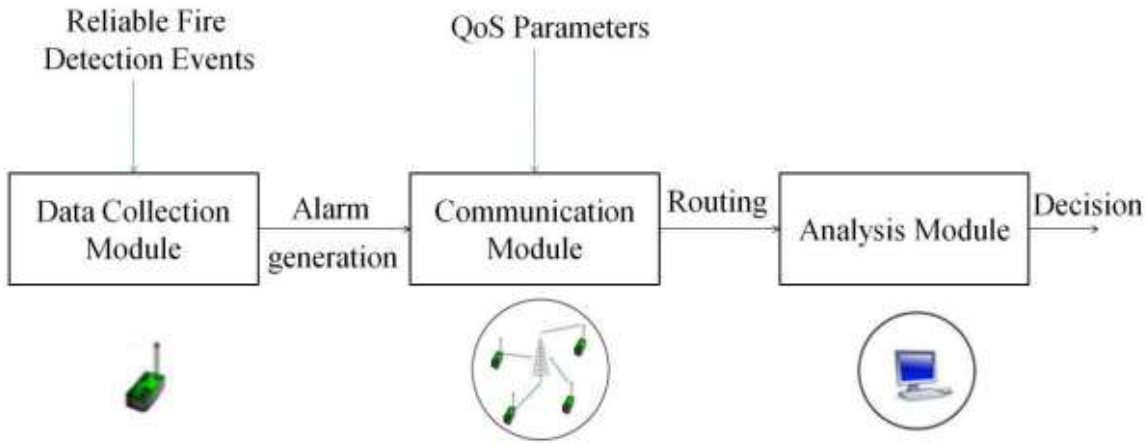

Figure.2. Adopted methodology of the forest fire detection process

The approach used for the WSN-based forest fire systems is shown in the above graphic. Three distinct stages make up the system's operation. In the first stage, sensor modules are positioned in the desired region to continuously monitor the environment. The sensor will continue to function normally up until a fire occurs. The sensor nodes monitor things like temperature, humidity, light intensity, and gases. The communication module, which is part of the second phase, is in charge of sending essential information, such as alerts, events, or any detected data, to the analysis module while taking specific quality of service characteristics into account. Reliability (an event must reach the coordinate node securely), temporal constraint (an event must take sufficient time to reach the destination), and security are among the QoS characteristics that are taken into account (the path must be secure from any attack). The analysis module, which is in charge of looking over the received alerts, is in charge of functioning in the third phase. The decision-making centre then processes the detected data and determines whether or not an alert is false. By removing the overhead present throughout the transmission process, the sensor node has the capacity to identify nearby woods. The sensor node that is capable of picking up on fire occurrences will function as active sensors. This makes an attempt to deliver the data via the cluster head and gateway to the sink node.

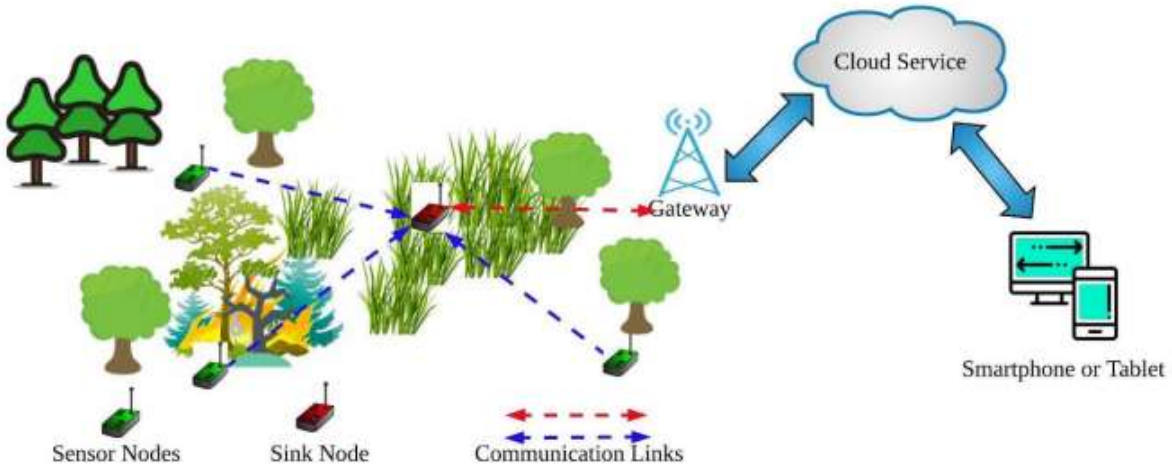

Figure.3: Sensor deployment and information transmission

The Figure.3 above top. explains the process of information transfer and sensor deployment. The sensor nodes, sink nodes, gateway, and smartphone with cloud-assisted services make up this system. The number of sensor modules is distributed randomly, and the forest's sensing field is established. The following section contains information about the sensor node's hardware. The deployed sensor node gathers the data and uses a gateway to interact with the sink nodes. Then, the activities taking place in the forest are watched over using cloud-assisted gadgets. A characteristic that characterises the forest has a significant value, I. It emphasises how crucial it is to save the forest from fire. Think of a situation where a forest is better protected because it is near a cultural heritage monument. The protection's perimeter is determined by the value of I. It stores the value on a scale of 1 to 10, with 1 denoting "not significant" and 10 denoting "very essential."

4. Data Collection and Communication Module

The factors of the forest environment, including humidity, light intensity, gases, and ambient temperature, are measured by the sensor nodes after they have been installed. Thinkspeak, an IoT-based cloud analytics solution that intends to store the sensed data under cloud channels, supports it. Figure. 4 depicts the data collection phase, during which field data is sent to the cloud server through a sink node for storage and real-time analysis. Field data is gathered, tracked, and stored in real time using the ThingSpeak cloud analytics platform. Data may be retrieved at any time and for any reason. Every two to three minutes, entries of environmental sensed variables are recorded in the cloud analytics platform ThingSpeak. The user at the control station may utilise algorithms to link the sensor network and controller by seeing the most current entries in graphical form. Each measurement's data is kept in a specific field, and the channel ID indicates different field attributes. Through the ThingSpeak channel on the Internet, the environment's real-time data is monitored. The user may at any time alter the field data and status depending on the analysis.

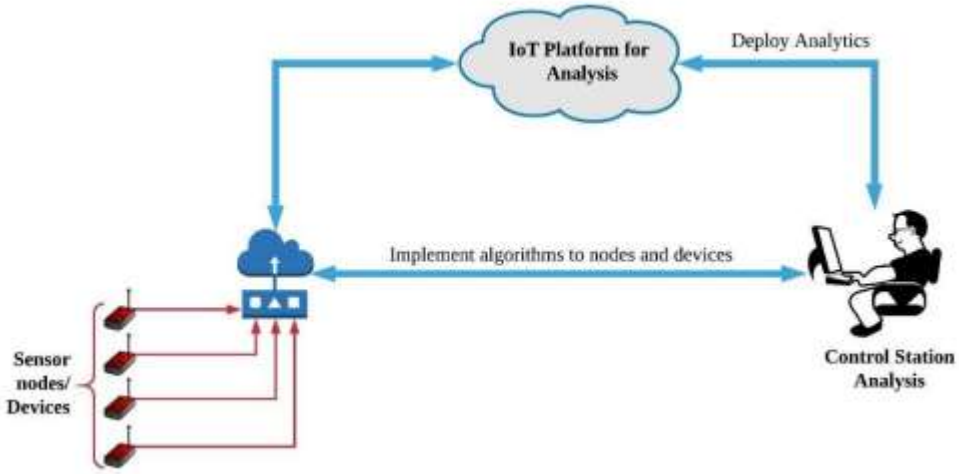

Figure.4: Data collection and storing using ThingSpeak cloud analytics platform

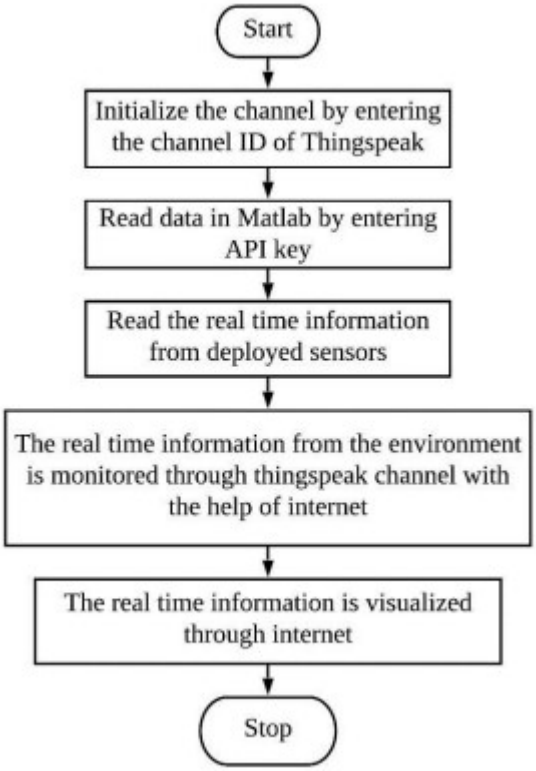

Figure.5: Flowchart of data collection and communication module

The workflow flowchart for data collecting using ThingSpeak analytics is shown in Figure.5. The reading of detected environmental factors comes after the channel startup, which creates the channel. The ThingSpeak platform's MATLAB interface enables real-time data reading and monitoring utilising Channel ID and API credentials. The newest items are updated in the cloud by the MATLAB code, which reads the channel ID. A MATLAB programme is used to run graphical plots of the real-time data. The last step is updating the channel with the field parameters and status. The acquired dataset must be configured in a way that reduces the anticipated fire

detection time. There are two states, namely regular states and abnormal states. The lack of data that differ from the default values, which indicates that the environment is safe, characterises normal circumstances. The other, however, is characterised by abnormal circumstances that mandate the existence of values that depart from the norm and indicate an unsafe setting. The Monitoring Centers take prompt action based on the Important value if any deviating values are discovered (I). The sensor nodes support the adaptive (or) external settings to do this. The sample rate of the sensing parameters is changed to improve the system's fidelity based on the environmental circumstances. An alert is created and sent through gateway to the monitoring module whenever any incident is discovered. The analysis step then verifies the warning that was produced.

5. Results and Discussion

Sensor nodes are placed in the forest area both randomly and deterministically to evaluate the effectiveness of the proposed model for detecting forest fires. Regular environmental monitoring is required to gauge the current condition of the area in order to make an early forecast of a fire outbreak. The deployed sensor modules gather ambient temperature, atmospheric gases, light intensity, humidity, and light intensity from the area of interest and send the data to a control centre for analysis. The only way to prevent the cause of wildfires and lessen their impact is via early fire event prediction. By continuously monitoring the environment, WSNs effectively forecast fire events in their earliest stages. The ground workers can get the timely notifications and act accordingly to avoid fires and put out other emergencies.

Figure.6: (a, b, c, d, e): Deployment of sensor nodes for collection of environmental parameters (a) Temperature & Humidity, (b) Smoke 1, (c) Light Intensity, (d) Smoke 2 and (e) Sink node

Figure 6 shows the placement of sensor modules to collect environmental data under typical atmospheric conditions. In Figure.6, (a) stands for the HTS-220 sensor node, which measures temperature and humidity, (b and d) for the MQ-2 sensor, which detects smoke particles in the environment, (c) for the TL sensor, which measures light intensity, and (e) for the sink node, which collects all sensed data. Each of these sensor nodes is placed in a distinct area that is within the sink node's transmission range and wirelessly transmits measured data to the coordinator node. The Fibocom G510 GPRS modules serve as the sink node, sending all detected data to a cloud platform for analysis and storage. The deployed sensor technology gathers environmental parameter information to identify potential enemies. The HTS-220 light sensor is a simple, affordably priced sensor that monitors light intensity. The examination of energy consumption and WSN lifetime is significantly impacted by the sink node, which is located in the centre of the area of interest. The sink node is configured to provide the cloud server the most current field data entries every two to five minutes. In the field, sensors and an intelligent sensor gateway module are used to track a variety of characteristics, including humidity, light intensity, gases, and ambient temperature. The data was collected using the deployed sensor nodes and saved in the cloud for processing. Using the ThingSpeak IoT Application, data gathered from these sensors is saved in the cloud. The measured values of humidity, light intensity, gases, and ambient temperature are shown in the table for each time occurrence. For data collection during the experiment in a live outside area, simulation is used. In order to gather and save data in a real-time context, the ThingSpeak IoT analytics is employed, and associated difficulties are noted. Several graphical charts for humidity, light intensity, gases, and ambient temperature have been created using the ThingSpeak IoT analytics on the basis of the observed information. Figure.7 depicts the analysis and verification of the sensor readings in ThingSpeak.

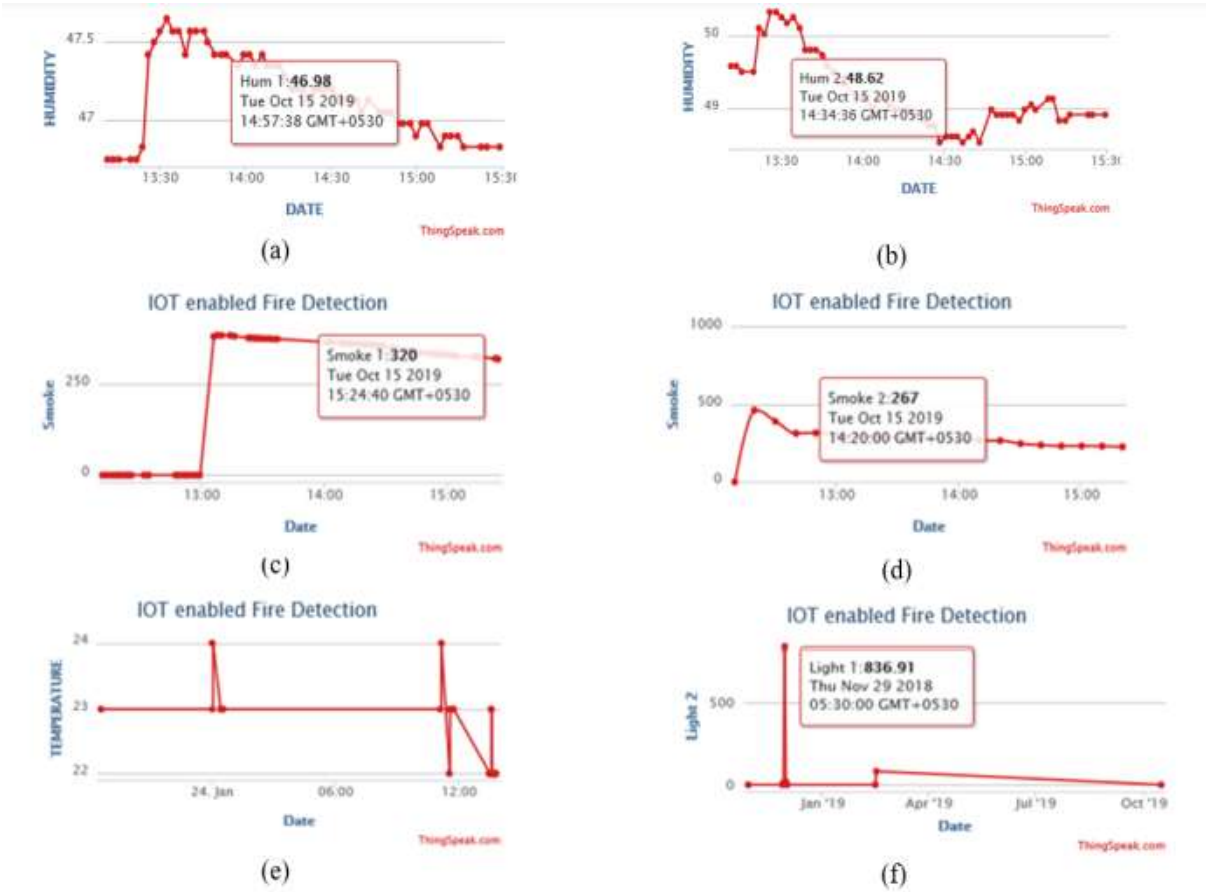

Figure.7: Obtained results from Thingspeak IoT analytics for various field set as (a & b): Humidity (in %), (c & d): Smoke (in ppm), (e): Temperature (in °C), (f): Light (in lux)

The graphical representation of several recorded environmental parameters is shown in the above image. It depicts the fluctuations of characteristics including humidity, light intensity, gases, and ambient temperature as well as the output results of the data gathered from the ThingSpeak cloud. Given that data updates on Think speak take a few seconds, it detects in almost real time. Figuring 7. The plot of recorded humidity values at two separate locations is shown in (a & b), the plot of recorded smoke values at two different locations is shown in (c & d), and the plot of temperature and light intensity from two different locations is shown in (e & f). When monitoring the status of the environment, the cloud platform offers a clear verification and analysis of all sensor information. By generating channel field sets, the MATLAB interface of cloud platforms enables real-time monitoring as well as the display of multiple sensor readings in graphical representation. The installed sensors gather data in real time, however there is a little lag before the data is updated on the ThinkSpeak cloud platform.

6. Conclusion

Researchers are paying a lot of attention to early forest fire detection. Recent years have seen an increase in awareness of the need to protect biodiversity, which has led to innovative planning techniques for controlling forest fires. Real-time applications should focus on creating an effective

nodes deployment method. This chapter explores efficient data collecting and real-time data processing since an efficient design will improve the performance of the systems. This study's major objective is to use WSNs to monitor the forest ecosystem. The detected information, such as humidity, light intensity, atmospheric gases, and ambient temperature from a real-time environment, is managed by Thingspeak, an IoT-based cloud analytics platform. This chapter explores how decisions are made in the case of a fire, including the collection, monitoring, and real-time analysis of measured data. The suggested system effectively monitors forest fires using sensors and the cloud-based IoT platform ThingSpeak. Real-time transmission to the ThingSpeak cloud of sensor data for temperature, humidity, light intensity, and gases. The system has the ability to gather, track, and analyse data for decision-making. The system provides an excellent solution for the early identification of fire incidents and is useful for the real-time study of environmental factors.

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