EMERGING METHODS FOR EARLY DETECTION OF FOREST FIRE USING IOT

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ABSTRACT

Everyone is aware that the forest is one of the most important and necessary resources and that forest fires pose a constant threat to biological systems, features of systems, and the environment. The necessity to identify forest fires as quickly as possible is urgent because the identification of forest fires has grown to be a crucial problem in the pre-suppression process. This literal work has made a strong case for the skilled use of wireless sensor networks as a plausible explanation for the cause of forest fires. To complete the solution process, the suggested system relies on a variety of sensors that are attached to it as well as data from these mediums of wireless communication. These sensor data are transmitted by the devices that are used for detecting the early occurrence of fire in the rich forest and alerting the fire department as well as the forest department, who will examine and prevent the situation as early as possible.

Keywords - GSM, Humidity, Flame, Smoke, Temperature, and Wireless Sensor Network.

1. INTRODUCTION

Forest fires do substantial damage to flora, air pollution, and human life. The purpose of this project is to develop a fire alarm system with enhanced capabilities for monitoring and detecting forest fires, such as the ability to link data from the forest for analysis and early detection of flames. The heavily charred soil becomes water resistive, and the earth can no longer absorb any more water, causing a reduction in groundwater level and contaminating the river's water. Forest fires are highlighted as one of the primary drivers of global warming in the 2008 Global Warming Report owing to the large amount of greenhouse gases emitted into the sky. Applications such as event detection [1], forest fire detection [2], surveillance systems [3], [4], localization of oil leakages [5] etc. With multimodal wireless sensor networks (WSNs) and/or the Internet of Things (IoT), precise event inference is the primary driver. However, accuracy in such a scenario is difficult to achieve, because of the following two reasons:

1.1 Data Redundancy

In practise, numerous events occur concurrently, resulting in a massive amount of data at the reporting node. This massive amount of data comprises events from various sources that must be analysed and categorised before any conclusions can be drawn.

Consider the following scenario: sensor nodes are charged with reporting the noises of various animals in a defined area in a forest zone. At any given time, each node may report several occurrences; yet, the nodes are unable to distinguish between the sounds produced by various animals. As a consequence, the recorded signal may include samples from numerous animals as well as some noise, but it is presented as a single sound signal. This event categorization challenge in WSN and IoT networks is known as the problem of mixed sound event verification, and it is addressed in the first half of this work's problem description.

1.2 Unreliable Inference

The second and less studied issue is that the accuracy of event detection at each node is reliant on the node's relative location from the event, making it unreliable. Imagine an alternative scenario, such as a forest fire, where the intensity of the event (in this case, the forest fire) varies depending on the position of the sensor node. Intuitively, nodes nearest to the event have the best observation, whereas nodes farther away from the event observe it with less intensity. Hence, if the nodes' sensing range (RS) is 30 metres (m) and the distance between two nodes from the same event is 2 and 25 metres (m), respectively. Then, all nodes that are within the sensing range of the event can detect and report. Yet, the node 2 m away from the event may report the likelihood of forest fire as x, while the node 25 m away from the event may record the identical event with a probability of as y, implying that x!= y. As a result, the authenticity of event reporting is undermined in such instances, resulting in arbitrary inference from observed data. Given that many actual WSN and IoT applications are driven by multimodal data, such as audio, video, and pictures, research in the domain of multimodal event detection and inference has resulted in some extremely intriguing results and techniques. To use an example, the authors of [6] intend to track the speakers in a closed, congested, and covered setting using auditory and visual cues. Another study in [7] employs multimodal sensor data for human behaviour recognition. To accomplish their goal, the writers employ pictures, acceleration, and sound cues.

Several comparable efforts, such as [8]-[10] and many more, employed multimodal data for incident detection in assisted living facilities, traffic management, and monitoring and reporting of old individuals at home. Other notable efforts include those given in [11], [12], in which sound sensors are utilised to assist hearing-impaired people. A motivated research survey, [13], provides a thorough examination of the work done in multimodal event discrimination and inference. A detailed analysis of the literature reveals that recent developments in event detection have taken into account the problem of event discrimination favourably. For example, the blind source separation (BSS) approach has been widely utilised and optimised throughout the years. [14], [15]. A uncontrolled forest fire is one of the most hazardous natural hazards, wreaking havoc on the ecosystem and threatening public safety. As a result of climate change, such as global warming, heat waves and droughts have grown increasingly regular in recent years, resulting in devastating forest fires. For example, on March 30th, 2019, a forest fire broke out in Liangshan. China caused such massive losses in terms of firefighter life and forest resources. If the forest fire was discovered in its early stages, the losses may be mitigated. In recent years, there has been a lot of interest in early fire detection approaches based on computer vision.

Conventional detection algorithms make extensive use of many colour and spatial areas. Some methods combine the colour and dynamic characteristics of the flame to obtain more reliable identification. Despite the fact that countless research on fire detection have been undertaken, only a few studies have taken into consideration the forest environment. Unmanned aerial vehicle (UAV) on the other hand, has become a highly efficient platform with applicability to different activities during the preceding decade due to its adaptability and low cost. Sadly, just a few studies have used unmanned aerial vehicles (UAVs) to monitor and identify forest fires. In this article, the UAV is used to collect images of the forest environment, allowing a greater search area to be covered. Deep learning is rapidly evolving as computer technology, particularly graphics processing units, advances (GPUs).

Because of its extraordinary ability in classification and object recognition, deep learning has lately been used for forest fire detection. To create a fire detection technique, researchers used two pre-trained deep convolutional neural networks (CNNs), VGG16 and Resnet50. Zhang et al. developed a forest fire detection model that combines a whole picture CNN and a local patch NN classifier, followed by a faster region-based CNN to recognise wild forest fire smoke. Shen et al. developed a flame detection system based on the YOLO (You Only Look Once) approach. Likewise, Barmpoutis et al.

A method for detecting fires in photos that combines the benefits of deep learning and spatial texture analysis was demonstrated. This study proposed a deep-learning-based forest fire detection system, with the objective of improving detection precision and efficiency through the use of a versatile UAV platform. Initially, a large-scale YOLOv3 network is used to build a fire detection system. The algorithm is then applied to the UAV-based forest fire detection platform. The photographs taken by the UAV are transmitted back to the ground station, where they may be analysed with great precision in real time using the proposed YOLOv3 algorithm on the high-performance computer at the ground station.

2. LITERATURE SURVEY

[1] Optimization Of Sugeno Fuzzy Logic Based On Wireless Sensor Network In Forest Fire Monitoring System. Author - Setiyo Budiyanto, Ucuk Darusalam. Year – 2020.

Forest fires are a type of natural catastrophe that occurs frequently in Indonesia and is a local and worldwide issue. Today's forest fires are mostly caused by two sources. Natural influences and uncontrolled human activity factors are two examples. As a result, the goal of this research is to develop solutions to lessen the number of forest fires that occur today. As a result, a fire detection system with a dual sensor-based wireless sensor network based on the Sugeno FIS (Fuzzy Inference System) algorithm that can be accessible over the Internet network is built. The goal of this study is to use WSN to develop a forest fire monitoring system for a large region of fire-prone areas (Wireless Sensor Network).

PROS

• Forest fires help to kill disease that can impact the biome.

• Fire detection and calculation of its intensity, and tracking of the desired location.

• Utilizing digital media with Internet connectivity as a media monitoring system.

CONS

• Forest fires can be overly destructive in their work.

• Forest fires can burn more than trees.

• Forest fires can create health problems for people.

[2] Fully Smart fire detection and prevention in the authorized forests. Author - S.Hrushikesava Raju , S.Kavitha. Year – 2021.

Fires can now develop suddenly in woods due to a variety of external sources. To identify and preserve plants and animals, the suggested system implements an unique model that includes the integration of a few sensors for detecting fires and alerting the nearest communication centre. This system also links to ponds to harvest water and water pipes near woods, activating such entities to convey water to the greatest degree feasible in order to avoid harmful circumstances. The cameras with fixed sensors will watch the sceneries and, if a fire component is discovered, will activate the remaining modules to avoid becoming harmful. The goal is to conserve the plants since they will provide rain and oxygen.

PROS

• Usage of sensors.

• Satellite images.

• Fire detection and calculation of its intensity, and tracking of the desired location.

CONS

• Forest fires can trigger mudslides, landslides, and other forms of erosion.

• Forest fires can devastate the ecosystem.

• Forest fires can start on their own.

[3] Forest Monitoring System for Early Fire Detection Based on Convolutional Neural Network and UAV imagery. Author - Georgi Dimitrov Georgiev, Georgi Hristov, Plamen Zahariev. Year – 2020.

One of the biggest causes of environmental damage is forest fires. The flames are difficult to find in their early stages, so a quicker and more precise detection approach can reduce the amount of damage they can do. In this study, we offer a method for autonomous early fire detection that relies on a system that is very reliable and doesn't require maintenance or human input. We created an object identification approach based on a convolutional neural network, which is discussed in the paper's main body, to provide the suggested system the autonomous capabilities.

PROS

• Usage of sensors.

• Satellite images.

• Forest fires help to kill disease that can impact the biome.

CONS

• Forest fires can be overly destructive in their work.

• Forest fires can burn more than trees.

• Forest fires can create health problems for people.

[4] A YOLOv3-based Learning Strategy for Real-time UAV-based Forest Fire Detection. Author - Zhentian Jiao, Youmin Zhang, Lingxia Mu. Year – 2020.

Safety of forest resources is crucial for maintaining both public and ecological security. Although forest fire detection techniques have received a lot of attention recently, their performance in terms of thoroughness, speed, and accuracy is still unsatisfactory. In this work, a deep learning fire detection method is developed with the goal of the effectiveness and precision of deploying the unmanned aerial vehicle for detection (UAV). First, a massive YOLOv3 network is created to guarantee detection accuracy. The algorithm is then used on the platform for UAV forest fire detection (UAV-FFD), which allows for real-time transmission of fire photos from the UAV to the base station.

PROS

• Usage of sensors.

• Satellite images.

• Forest fires help to encourage change in the biome.

CONS

• Forest fires can trigger mudslides, landslides, and other forms of erosion.

• Forest fires can devastate the ecosystem.

• Forest fires can start on their own.

[5] Forest fire detection system based on Fuzzy Kalman filter. Author - Jianshuo Hu , Jing Song. Year – 2020.

The elements that start fires in big forests are unpredictable and non-linear. If only one sensor is used to gather data or if just one sensor is used to interpret data from several sensors, the Low detection effectiveness. We suggest a forest fire detection system based on fuzzy kalman filter in order to correctly fuse the multi-sensor data and identify the fire for the first time throughout the detection phase of forest fires. First, we combine a range of sensors and embedded processors into a fire warning system. Then, we preprocess the collected data and feed them into the Kalman filter for filter fusion. Finally, we do fuzzy reasoning on the likelihood of an open flame and a smouldering fire.

PROS

• Usage of sensors.

• Forest fires can help to stop wildfires.

• Forest fires help to encourage change in the biome.

CONS

• Forest fires can be overly destructive in their work.

• Forest fires can burn more than trees.

• Forest fires can create health problems for people.

2. EXISTING METHODOLOGY:

Quick response to a fire breakout is the only option to avoid large losses and environmental and resource harm in this forest fire detection system employing IOT. As a result, the most essential tasks of fire surveillance are to identify fires quickly and reliably and to warn the forest service. It is considerably easier to put out a fire when the origin is recognised and it is at its susceptible stage. Knowledge on the course of the fire is also extremely useful for managing the fire at all stages. According to this information.

3. RELATED WORK

Kalli Srinivasa Nageswara Prasad et al. [16] suggested a unique approach for automatically detecting forest fires using geographical data pertaining to forest zones using clustering and fuzzy logic. They examine two successive frames for dispersion in coordinate (minimum and maximum) of X and Y, then compare to an area detection model. Gaurav Yadav et al. [18] optimise a fire detection technique by recognising grey cycle pixels near the flame. They suggested an unique fire detection system based on colour detection, which includes motion detection, grey cycle detection, and area dispersion, with a final system performance of 92.31%. They claim that their system uses fewer false alarms and improves system performance. Sam G.Benjaminetal., [19] summarises many strategies that significantly minimise the false detection rate. These authors believe that combining many approaches is necessary to achieve superior detection results. They demonstrate that approaches based on colour cues, motion analysis, and fire flickering outperform those based just on colour information.

Anupam Mittal et al. [20] provide an overview of machine learning algorithms for detecting fires. Readers are introduced to SVM, ANN, DT, and FFNN. F. Sunar et al. [21] evaluate the potential of boosting classification technique for forest fire detection using SPOT-4 photos. Classification accuracy is used to evaluate 5 classifications: Multi Layer Perception (MLP), Maximum Likelihood (ML), Adaboost (AB), Logitboost (LB), and Regression Tree (RT). The findings indicate that AB and LB classifications might be a viable alternative to traditional approaches. Qingjie Zhang et al. [22] provide a deep learning system for detecting forest fires. They used a cascaded approach to fire detection, with the global imagelevel testing the entire image first, and the fine grained patch classifier detecting the specific spot of the identified fire. They presented a baseline for fire detection, 178 photos for the train set, and 59 images for the test set. They use the CIFAR 10 network for the first stage, but reduce the number of outputs by two and add a drop out layer to minimise overfitting.

They employ the Caffe framework's 8-layer AlexNet for the second step. Our work focuses on real-time forest fire/smoke detection, and we conduct the tests using the three approaches indicated above as well as one modified YOLO algorithm. According to the results, SSD has the best performance and real-time properties. We refine the original tiny-yolo-voc and get a new structure, tiny-yolo-voc1, which outperforms yolo-voc.2.0 and tiny-yolo-voc in detection accuracy. We concentrate on tiny/dark fire/smoke real-time detection; although the revised structure of YOLO has real-time properties, poor performance in small fires forces us to discard it in favour of SSD.

DRAWBACKS: This system's technique makes early identification of fire burnout in the forest challenging.

4. PROPOSED METHODOLOGY:

A suggested system for forest fire detection based on wireless sensors and machine learning was discovered to be an effective approach for forest fire detection. To produce a more accurate result with the least amount of delay, the analysis begins with the inputs (Data) of both the sensors and the picture, which is collected using a camera as a digital component. A solution is easily implementable as a freestanding system for extended periods of time, with the primary power source provided by rechargeable batteries and a secondary solar power supply. We advocated using current technology to detect forest fires using this way. The system is intended to identify and alert forest officers about forest fires. The system's operations are controlled by a microprocessor, and various sensors are utilised to detect forest fires. When a fire is found, its specific location is determined and sent to a nearby forest ranger.

As a result, the system is a complete IoT-based system in which the system's activities are constantly monitored and the monitoring information is kept in web pages that the officer checks on a regular basis. The data is preserved so that it may be viewed at any time. The graphic depicts the block diagram of the proposed system. A solar panel with a battery is used to power the system in this example. Because the system is designed to be deployed in the forest, power cannot be delivered via transmission lines; instead, a solar panel is used to charge and store energy in a battery. It is identified as a source by the system. The Arduino, which controls everything, is a key component of this system. It is linked to a variety of sensors, including a temperature and smoke sensor. The temperature sensor monitors the temperature of the forest, while the smoke sensor measures the amount of smoke in the forest. The temperature sensor detects a steady rise in temperature during a fire. The smoke level increases during a forest fire. As a consequence, the Arduino, where the sensors are connected, continuously checks the value rise. When the temperature hits a certain threshold, the Arduino performs its function and sends data on the forest fire. This Arduino is connected to a wireless network.

A GPS module as well as a module. The Wi-Fi module has an ESP8266 component, which has various unique properties that are used to transfer data to authorities through the cloud or online mode. To send information about the forest fire, an internet connection is required. This ESP8266 may function as a client like Wi-Fi, a server like hotspots, or both as a client and a server at the same time. As a result, the various systems may be connected together to create a chain reaction. A GPS module is also used, which detects and locates the exact location of the fire. The system offers the fire's location as well as latitude and longitude information, which may be used to locate the exact site of the fire. In this scenario, IoT is used to monitor and collect data about a forest fire. Monitoring activities are carried out on a regular basis at this site, regardless of whether or not there is a forest fire. The monitoring system is implemented in the surrounding area, such as at the forest office or nearby fire stations.

The system's details are linked to an office computer system that the officer may monitor. Measurement of rainfall in the forest, humidity in the forest, and other capabilities might be added to the system. The systems are linked in a chain reaction, and if one system fails, the chain reaction breaks, causing damage.

5. Algorithms Used:

5. [1] YOLO Algorithm

YOLO is a neural network-based real-time object detection technology. The speed and precision of this method are well-known. It has been used to identify traffic lights, pedestrians, parking metres, and animals in a variety of applications. You Only Look Once is an acronym for the phrase "You Only Look Once." This is an algorithm that finds and recognises different things in a photograph (in real-time). YOLO performs object detection as a regression problem and returns the class probabilities of the discovered photos. To detect objects in real-time, the YOLO method leverages convolutional neural networks (CNN). To identify objects, the approach requires just one forward propagation through a neural network, as the name implies. This means that the entire image may be anticipated in a single algorithm run. The CNN is used to forecast several class probabilities and bounding boxes at the same time. The YOLO algorithm has several variations. Little YOLO and YOLOv3 are two popular examples.

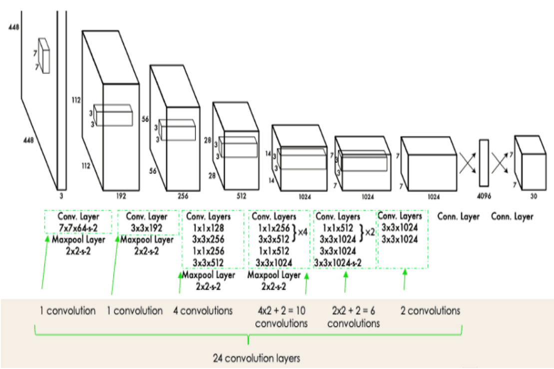
Steps:

1. Classification.
2. Localization.
3. Detection.

The algorithm is based on four approaches:

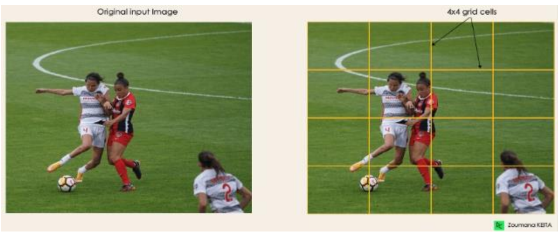
1. Residual blocks
2. Bounding box regression
3. Intersection Over Unions or IOU for short
4. Non-Maximum Suppression.

YOLO Architecture



1. Residual blocks

The first step is to divide the original image (A) into NXN grid cells of equal size, where N equals 4, as seen on the right image. Each grid cell is in charge of determining and forecasting the item class it covers, as well as the probability/confidence value.



2. Bounding box regression

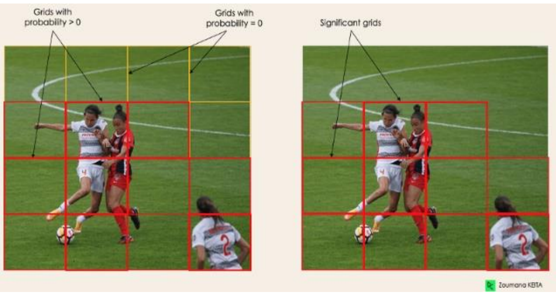
The following step is to find the bounding boxes, which are rectangles that highlight all of the things in the image. A image can have as many bounding boxes as there are items. The properties of these bounding boxes are determined by YOLO using a single regression module in the following manner, where Y indicates the final vector representation of each bounding box.

Y is equal to [pc, bx, by, bh, bw, c1, c2].

This is especially critical during the model's training phase.

pc is the probability score of an object in a grid.

For example, all grids in red will have a probability greater than zero. Because the chance of each yellow cell is zero, the picture on the right shows a simplified version (insignificant). The x and y coordinates of the centre of the bounding box with respect to the surrounding grid cell are given by bx, by. bh and bw are the height and breadth of the bounding box in relation to the surrounding grid cell. cl and c2 represent the classes Player and Ball, respectively. We can have as many courses as your application necessitates.



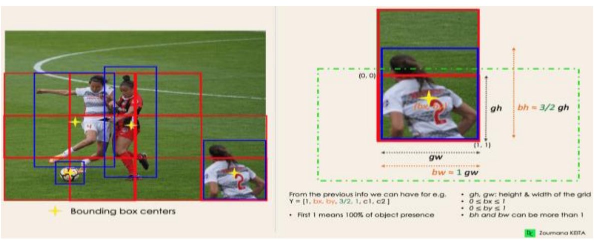
3. Intersection Over Unions or IOU

A single item in a picture might often have several grid box candidates for prediction, even if not all of them are significant. The IOU (a value between 0 and 1)'s purpose is to reject such grid boxes and maintain only those that are useful. The reasoning is as follows:

The user specifies the IOU selection threshold, which may be as low as 0.5.

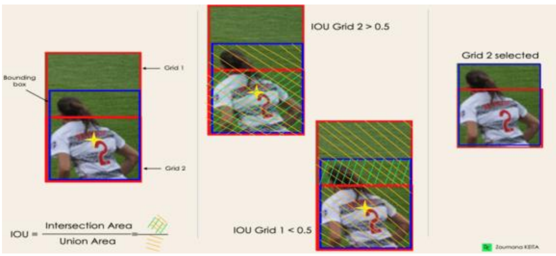
The IOU of each grid cell is then computed using YOLO, which is the Intersection Area divided by the Union Area.

Lastly, it disregards the forecast of grid cells with an IOU threshold in favour of those with an IOU > threshold.



4. Non-Max Suppression or NMS

Establishing an IOU threshold is not always sufficient since an item might have numerous boxes with IOU over the threshold, and leaving all of those boxes may include noise. Now, we may apply NMS to preserve only the boxes with the greatest detection probability score.



IMPLEMENTATION IMAGES:

5. [2] Haar Cascade Algorithm

Object detection is a computer approach for detecting occurrences of objects in photos and films. It has applications in computer vision, image processing, and deep learning. We shall identify items in this article using a technique called as haar cascades. Haar Cascade classifiers are a fast way to detect things. In their work Haar Cascade classifiers provide an efficient approach for object detection, Paul Viola and Michael Jones proposed this technique. This method was proposed by Paul Viola and Michael Jones in their work Fast Item Identification Using a Boosted Cascade of Basic Characteristics. Haar Cascade is a machine learning-based strategy that trains the classifier with a huge number of positive and negative images.

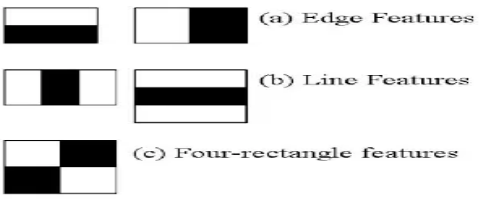
Positive images – These are the photographs that we want our classifier to recognise.

Negative Images – Pictures of everything else that isn't the object we're looking for.

Understanding project Algorithm:

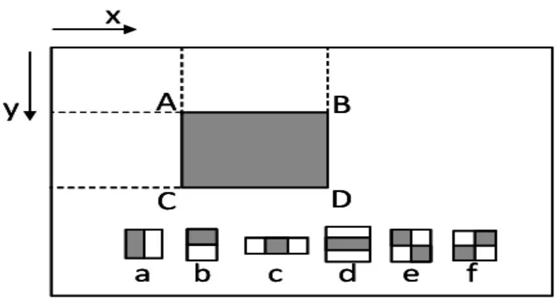
Let us break down our idea into simple steps and create an algorithm for it.

1. Importing OpenCV
2. Importing XML file
3. Importing test Image
4. Converting the image to grayscale
5. Detecting Multi-scale images
6. Mentioning sides of the rectangle for fire detection
7. Displaying the detected image.



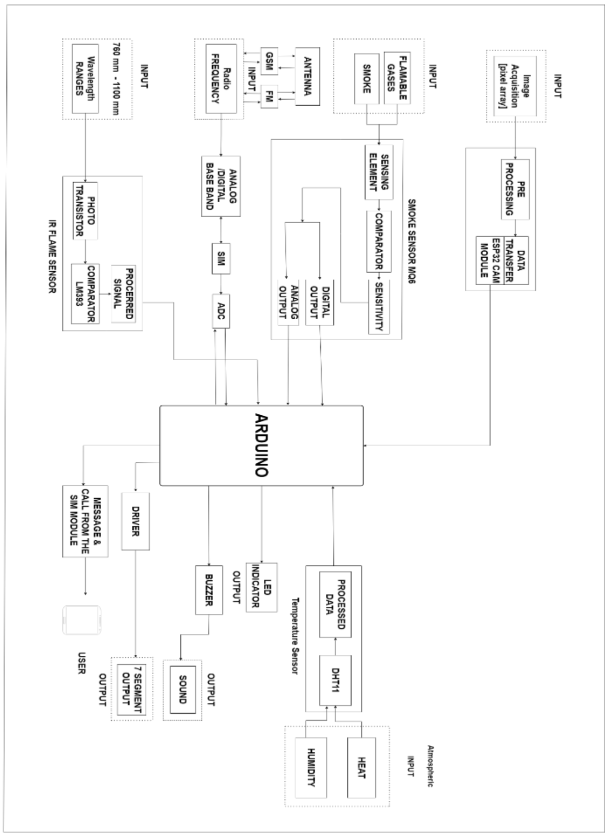
Creating Integral Images

Without getting into too much detail about the mathematics (see the paper if you're interested), integral pictures basically accelerate the calculation of these Haar characteristics. Rather than computing at each pixel, it constructs sub-rectangles and array references for each of those sub-rectangles. After that, the Haar characteristics are computed.



Advantage: Early detection of fire burnout in forest is difficult to identify using this methodology of system.

6. ARCHITECTURE DIAGRAM



7. Components Used:

1. Arduino module.
2. Wi-Fi module.
3. GPS module.

7. [1] ARDUINO MODULE

Arduino is a microcontroller board that controls and monitors system activities. The Arduino used in this project is the Arduino UNO R3. The Arduino Uno R3 is an ATmega328-based microcontroller board. It contains 14 digital I/O pins, six analogue inputs, a crystal oscillator with a frequency of 16 MHz, a USB connection, a power connector, and an ICSP header, and a reset button. It comes with everything you need to get started with the microcontroller; just plug it into a computer via USB or power it with an AC-to-DC converter or battery. Memory on the ATmega328 is 32 KB (with 0.5 KB used for the boot loader). In addition, there is 2 KB of SRAM and 1 KB of EEPROM.

The Arduino is powered by a 5 volt power supply. The Arduino may be fuelled by USB or an external source. It selects the supply automatically. An adapter or batteries might be used as an external power source. An AC-to-DC converter was used as the adaptor. Any communication device, such as a computer, another Arduino, or other microcontrollers, may be linked to the Arduino. The AT mega 28 supports serial UART TTL (5V) connection through digital pins 0 (RX) and 1. (TX). Serial communication is handled by an ATmega16U2 on the board through USB and appears to apps on the computer as a virtual com port. Several sensors, including a temperature sensor and a smoke sensor, are connected to the Arduino.

7. [2] THE WI-FI MODULE:

The Wi-Fi module is one of the system modules that is used to carry data. The Arduino's data is transferred to the appropriate place via this Wi-Fi module. The Wi-Fi module used is the ESP8266. This is used to access a Wi-Fi network.

The Wi-Fi module may run an application or act as a wireless network. It may serve as both a client and a server. The Wi-Fi module can function as a hotspot, connecting other devices, or as a client, receiving network information from other processors. The ESP8266 may act as both a client and a server, or both simultaneously. This module sends information about a forest fire to a neighbouring region. Because the forest is vast, more systems must be linked so that this module may be linked as a chain system and any faults in the device can be identified fast.

7. [3] MODULE GPS:

The GPS module is utilised to track and precisely locate the forest fire. It is capable of instantly locating the location. It runs on 3-5 V and sends data at a rate of 9600 bps. It also has a backup battery that can store data if the power goes off.

This module is linked to the Arduino module; when the Arduino detects a fire using the temperature and smoke sensors, it communicates the information to the surrounding area through the Wi-Fi module, together with the GPS module's latitude and longitude data. Obtaining longitude and latitude information allows you to establish your exact location. In this scenario, GPS is used in conjunction with an aerial to calculate position values.

8. Modules:

8. [1] Eloquent Esp32cam–Camera

The ESP32-CAM is a low-power camera module based on the ESP32. It includes an OV2640 camera and an inbuilt TF card slot. This board has 4MB of PSRAM for buffering images from the camera into video streaming or other activities, allowing you to shoot higher-quality shots without crashing the ESP32. It also has an inbuilt LED for flashing and a number of GPIOs for connecting peripherals.

Features:

1.Onboard ESP32-S module, supports WiFi + Bluetooth
2.OV2640 camera with flash.
3.Onboard TF card slot, supports up to 4G TF card for data storage.
4. WiFi video surveillance and picture upload are both supported.
5. Offers many sleep modes and has a deep sleep current of as little as 6mA.

INPUT: FIRE TEST IMAGES.

OUTPUT: SMS, VOICE CALL, BUZZER SOUND, LED LIGHT, ALERT MESSAGE.

8. [2] SIM800L–SMS:

SIM800L GSM/GPRS module is a Simcom tiny cellular GSM modem that can readily interface with any microcontroller to provide GSM functionality and GPRS transmission. This module links the microcontroller to the mobile network so that it may make and receive phone calls, send and receive SMS (text messages), and connect to the internet through GPRS, TCP, or IP. Another benefit is that it supports a quad-band GSM/GPRS network, allowing it to function everywhere in the world. These vital features, as well as the low cost and small size, make this module ideal for any project requiring long-range communication, and it can also be integrated into a wide range of IoT applications.

INPUT: SIM CARD, ARDUINO.

OUTPUT: SMS, VOICE CALL.

8. [3] Gpsneo–GPS

GPS, which stands for Global Positioning System, may be used to calculate your position, time, and speed when travelling.

1. This module includes an external antenna as well as an EEPROM built in.

2 .Interface: RS232 TTL.

3. Power supply: 3V to 5V.

4. Defaultbaudrate: 9600 bps.

5. Works with standard NMEA sentences.

Several microcontroller boards are also compatible with the NEO-6M GPS module. To find out how to utilise the NEO-6M GPS module with the Raspberry Pi.

1. The module GND pin is connected to Arduino GND pin.

2. The module RX pin is connected to Arduino pin3.

3. The module TX pin is connected to Arduino pin4.

4. The VCC pin of the module is linked to the Arduino 5V pin.

INPUT:ARDUINO.

OUTPUT: GPS LOCATION SEND IN THE SMS.

8. [4] Flame Sensor:

A flame detector is a sensor that detects and responds to the presence of a flame or fire, thereby allowing for flame detection. Responses to detected flames may include sounding an alarm, disabling a fuel line (such as a propane or natural gas line), and triggering a fire suppression system, depending on the installation. When employed in applications such as industrial furnaces, their job is to offer assurance that the furnace is operating properly; they can be used to switch off the ignition system, but in many circumstances, they take no direct action other than warning the operator or control system. Because of the processes used to detect the flame, a flame detector may frequently respond faster and more precisely than a smoke or heat detector.

INPUT:FIRE.

OUTPUT: SMS, VOICE CALL, BUZZER SOUND, LED LIGHT, ALERT MESSAGE.

8. [5] Gas Sensor MQ6:

A smoke detector is a device that detects smoke as a signal of a fire. Smoke can be detected visually (photoelectrically) or physically (ionization). Detectors may employ either one or both sensing mechanisms. Smoking in prohibited locations may be detected and discouraged using sensitive alarms. Smoke detectors in large commercial and industrial buildings are often linked to a central fire alarm system.

INPUT: SMOKE.

OUTPUT: SMS, VOICE CALL, BUZZER SOUND, LED LIGHT, ALERT MESSAGE.

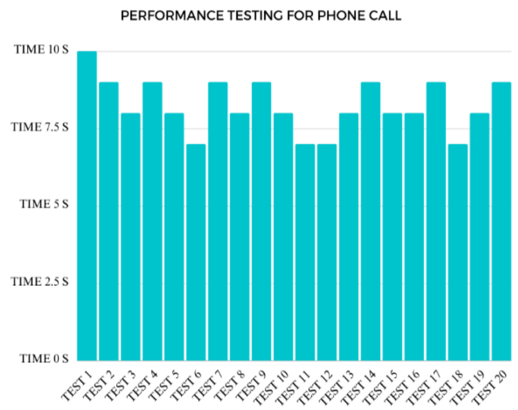
8. [6] Temperature and Humility DTL11:

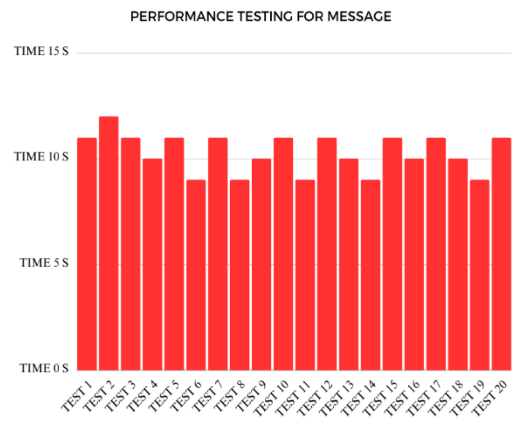
Temperature sensors are basic devices that detect the amount of cold or heat present and convert it into a simple unit. In our daily lives, we utilise them for a number of purposes, including household water heaters, refrigerators, microwaves, and thermometers. Temperature sensors are designed to keep a frequent check on particular infrastructure such as highway bridges, railway tracks, concrete or earth dams, and so on.

INPUT: TEMPERATURE.

OUTPUT: SMS, VOICE CALL, BUZZER SOUND, LED LIGHT, ALERT MESSAGE.

PERFORMANCE CHART:





9. ALGORITHM:

STEP BY STEP EXECUTIONS:

1. Initialize a temperature sensor to measure the current temperature.

2.Set up a loop to continuously measure the temperature and compare it to the threshold.

3.If the temperature exceeds the threshold, record the time and location of the temperature reading.

4.Use a decision-making algorithm to determine if the recorded temperature reading is indicative of a forest fire. This algorithm could take into account factors such as the duration of the high temperature reading, the location of the temperature reading, and any nearby sources of heat (such as a road or building).

5.If the algorithm determines that a forest fire is likely, send an alert to the appropriate authorities and initiate a response plan (such as dispatching firefighters or evacuating nearby residents).

6.If the algorithm determines that a forest fire is not likely, continue monitoring the temperature and recording any high readings.

7.When the program is no longer needed, stop the loop and shut down the temperature sensor.

10. RANGE OF SENSOR:

1. GAS SENSOR – 9 METER.

2. FLAME SENSOR – 4.4 MICROMETER.

3. TEMPERATURE AND HUMIDITY DTL11 – 20-90% RH.

11. Advantages:

1. As compared to the present method, the suggested approach identifies forest fires faster. It offers a more robust data capture feature.

2. The main advantage is that it lowers false alarms and has precision owing to the different sensors that are there.

3. It reduces human labour since it operates automatically.

4. This is fairly inexpensive and hence easily accessible.

5. The primary goal of our project is to send an alert message to the appropriate person via an app.

12. Disadvantages:

Electrical interference reduces the efficacy of the radio receiver. The biggest disadvantage is that it has a smaller coverage range region.

13. Applications:

1. Fire detection and management are critical components of safety.

2. As a result, the suggested system may be used in shopping malls, workplaces, and data centres, among other places.

14. Future Scope:

1. When a fire breaks out, an additional pump may be fitted to immediately distribute water.

2. Industrial sensors can also be utilised to improve range and accuracy.

15. Conclusion:

When a fire breaks out, a kit has been devised to guarantee that no additional harm is done to the woods. The Kit immediately sends a message to the user. Based on this information, firefighting personnel may be directed to stop fires before they reach cultural heritage sites.

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