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FOREST FIRE DETECTION USING MACHINE LEARNING

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Abstract: - Detection of forest fire should be fast and accurate as they may cause damage and destruction at a large scale. Recently, Amazon forest confronted a devastating forest fire which remained obscured for over 15 days. Hence resulting in huge loss of ecosystem and adversely affecting the global conditions. As the technology is developing, Wireless Sensor Networks (WSN) is gaining importance in recent research areas as it has shown its usefulness in warning disasters and save lives[1]. As soon as an unusual event is noticed in the networks, an event is detected through the sensor devices placed at distributed locations. This event detection information is passed to the base station and decision is taken. Due to the static configuration of such sensor data in WSN generally lead to false alarm generation [2]. In such a scenario we can use machine learning algorithms to prevent false alarm since they get configured efficiently in dynamic nature, that too automatically .Therefore for eliminating the static essence of WSN, we present a machine learning algorithm imbibed with WSN. In this paper, we propose a decision tree machine learning approach for detecting events.

Keywords-- *PIC Microcontroller, Speed, Distance, L293D Motor Driver, Ultrasonic sensor, LED Display, Buzzer.*

I INTRODUCTION

Forest fires are a matter of concern because they cause extensive damage to environment, property and human life. Hence, it is crucial to detect the forest fire at an earlier stage. This can help in saving flora and fauna of the region along with the resources. Also, it may help to control the spread of fire at initial phase. The task of monitoring the forests is difficult because of the vast territory and dense forest.

The wide ranging adverse ecological, economic and social impacts of forest fires including forest degradation are:

- loss of valuable wood resources
- deterioration of catchment areas
- loss of biodiversity and extermination of flora and fauna
- loss of wildlife habitation and exhaustion of wildlife
- global warming

The forest fire has become a threat to not only to the forest wealth but also flora and fauna and ecology of the environment of the region. The main cause of forest fires can be categorized under natural and man-made classes. High atmospheric temperature, lightening and dryness (low humidity) offer positive environment for a fire to start which are the natural causes for forest fire. The fire is also caused by Man-made sources like naked flame, cigarette, electric spark, etc [3].

Forest fire poses a great threat as they remain unnoticed for a long period till the effects comes to city. WSN is a technology which can be employed in real time to detect or predict such hazards. . A WSN generally consists of spatially disseminated autonomous sensors to keep watch on physical or environmental conditions such as temperature, sound, pressure, CO, CO2, smoke or pollutants etc. and transfer the data to base station. WSN consists of hundreds of nodes. Each sensor node is capable of sensing, computing and communicating. Each sensor node has several elements which are a) microcontroller, b) interfacing circuit of sensors, and c) battery (energy source). Through the intercommunication between these nodes and the base station, the message of event detection is reported.

Event detection by WSN can be used in various applications requiring spatially disseminated sensor nodes to transmit information about events to the base station at particular periods as the event is detected. The performance of event detection methodology will rely on the hardware and software capabilities of the small yet powerful nodes placed in robust environment [5].

In this paper we propose a decision tree machine learning approach for event detection. Various models have been generated. The performance of the proposed approach is determined in terms of complexity and accuracy [4].

II OBJECTIVES

The objective of the project is:

- To devise an algorithm which can help to detect forest fire in its early stage.
- To implement forest fire detection system using small and cheap sensor nodes.
- To make the probability of false alarms reduced.
- To build a system which is energy efficient in distributed environment and also efficient in performance.

III LITERATURE SURVEY

Forest fire detection and prevention are real problems faced by a number of countries. Different methods have been stated for monitoring the emergence of fires.

A. Watch Towers

In earlier days, the forest fires were detected by manual observations with watch towers installed in the isolated areas of forest. Though this method was accurate, it was not preferred due to manual restrictions.

B. Satellite—Based Systems

Earth orbiting satellites have been used for detection of forest fires. Unfortunately, these satellites can provide the images of regions of the earth's surface every two days which is a very long time for fire scanning. Also the weather conditions can affect the quality of satellite images.

C. Optical Sensors and Digital Camera

The use of optical sensors only provides a line of sight vision, where the vision can be blocked by high trees or hills. The Camera surveillance systems were also inefficient for forest fire detection because of short distance ranges.

D. Wireless Sensor Networks

The sensors sense physical as well as chemical parameters. The sensors can operate in a self-healing and self-organizing wireless networking environment. The major problem with this system is that there are high chances of false alarms due to lack of proper processing of the sensor data.

In this paper, we propose a method which processes the sensor data to predict fire accurately. The sensor nodes are provided with Wi-Fi devices and tested on grassy areas to sense temperature, humidity, pressure and various other physical parameters and send this data back to the base station. At the base station, the data is processed by a machine learning agent to give alarm.

IV PRESENT SCENARIO

In these days numbers of approaches have been proposed by various researchers which deal in distributed event Internet detection by using WSN. The primary idea for detection of event is to define a threshold value for given parameters like temperature, pressure etc [4]. An alarm or signal is generated when major difference is recorded between threshold value and sensor recorded value. Another type of Base Station Sensors methodology in event detection makes use of pattern matching or machine learning techniques. Pattern matching is conducted at the base station of the sensor networks in order to make the decision.

Support Vector Machines, feed forward Neural Networks and Naive Bayes method are few approaches which have been proposed by various researchers for event detection on individual sensor nodes. The Cougar approach uses declarative queries to get back the information from WSN. In this approach each individual node process the data before sending back the fetched information to the base station .A query outputs data into a tabular form that represents the gathered data in the specified time quantum. Whole operation is applied on the data transferred to the base station. Later an improvement was done by giving an array of algorithms that efficiently measures the join queries over static data in the network.

Approaches discussed above mark the problem of collection of data to process offline from various sensor nodes located at distant locations and introduced the techniques for storing data online for later use [4].

V SYSTEM SPECIFICATIONS

A. Hardware Specifications

1) **MQ2 Gas Sensor**
2) **DHT22 Humidity and Temperature Sensor**
3) **NodeMCU ESP8266 Microcontroller**

TABLE 1 HARDWARE SPECIFICATIONS

Sr. No.	Component Name	Specifications
1.	MQ2 Gas Sensor	Operating Voltage: 5V Preheat Duration: 20 seconds Sensitivity of Digital pin can be varied using potentiometer. Detection Gas: Hydrogen, CO, methane, Alcohol etc. The enveloped MQ2 have 6 pins, 4 of them are used to fetch signals, and other 2 used for providing heating current.

2.	DHT22 Humidity and Temperature Sensor	Operating Voltage: 3 to 5V Humidity Range: 0-100% with 2-5% accuracy Temperature Range: -40 to 125°C with ±0.5°C accuracy No more than 0.5Hz sampling rate. It consists of humidity sensing component, a NTC temperature sensor and IC on the back side of the sensor.
3.	NodeMCU	Operating Voltage: 3.3V 32-bit RISC CPU UARTs: 1 Digital I/O Pins: 16 SRAM: 128KB

B. Software Specifications

Google Colaboratory — Colaboratory is a free Jupyter notebook environment provided by Google where one can use free GPUs and TPUs which requires no setup and runs entirely in the cloud. The Jupyter Notebook is an open-source web application which allows to create and share documents that contain live code, equations, visualizations and narrative text[11]. A notebook is a list of cells. Cells contain either explanatory text or executable code and its output. With Colaboratory one can write and execute code, save and share their analyses, and access powerful computing resources.

VI METHODOLOGY

A. Block Diagram

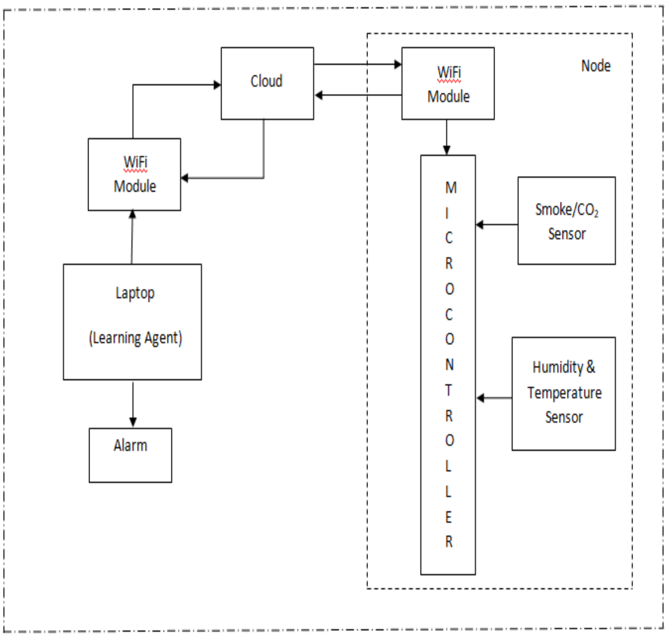

Figure 1 Block Diagram

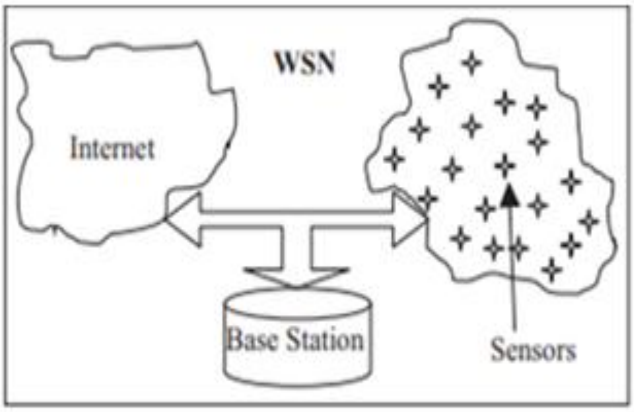

Figure 2 Pictorial Representation

Each node is comprised of microcontroller which has the following sensors and peripherals interfaced:

- Wi-Fi Module
- Smoke/Gas Sensor
- Humidity and Temperature Sensor

The idea is to create several such nodes. These nodes are distributed over the entire forest area. In our demonstration, we are presenting the functioning of a single node only.

The microcontroller samples data from each sensor at regular intervals. In between these sampling instants, the controller goes in sleep mode for the sake of power saving. The sampled data is sent over to the cloud and is stored there. The base station fetches the sensor data from the cloud storage. Base station has another processor (Laptops or desktops) which is the learning agent.

The agent is supervised learner. This means it has been already trained and the classifier model is ready. For the generation of classifier model, the agent uses decision tree learning algorithm.

So for each sampled data received from the nodes (via cloud), agent interpolates into the data space to determine forest fire. If the classifier model detects fire then the firefighters are alarmed.

B. Learning Algorithms

At its most basic, machine learning uses algorithms which accept and study input data to forecast output values for an acceptable range [9]. When new data is given to these algorithms, they learn and optimize their operations to enhance performance, developing 'intelligence' over time.

In supervised learning, examples are the references from which the machine is taught [8]. The operator provides the algorithm with a dataset that includes inputs and outputs, and the algorithm must find a method to determine how to reach at those inputs and outputs. In our experiments, we compared two algorithms namely Support Vector Machine (SVM) and Decision Tree.

1) Support Vector Machine (SVM) — In the SVM algorithm, we have to maximize the margin between the data points and the hyper plane. The hinge loss helps to maximize the margin [7].

$$c(x,y,\hat{f}(x)) = \begin{cases} & \text{if } y*f(x) > 0 \\ -y*f(x), & \text{else} \end{cases} \qquad (1)$$

$$c(x,y,f(x)) = (1 - y*f(x))_+ \qquad (2)$$

When the actual value and predicted value are of same sign then the cost is 0. We can calculate loss function if the values are not same. A regularization parameter is added to cost function. To balance the margin maximization and loss, the regularization parameter is used. The cost function is viewed as below after adding the regularization parameter.

$$min_w \lambda \parallel w \parallel^2 + \sum_{i=1}^{n} (1 - y_i \langle x_i, w \rangle)_+ \qquad (3)$$

The loss function for SVM

As we have the loss function, to find the gradients we take partial derivatives with respect to the weights. Weights can be updated by using the gradients.

$$\frac{\delta}{\delta w_k} \lambda \parallel w \parallel^2 = 2\lambda w_k$$

$$\frac{\delta}{\delta w_k} \left(1 - y_i \langle x_i, w \rangle\right)_+ = \begin{cases} 0, & \text{if } y_i \langle x_i, w \rangle \geq 1 \\ -y_i x_{ik}, & \text{else} \end{cases} \qquad (4)$$

Gradients

The model accurately predicts the class of data points i.e. no misclassification, from regularization parameter we have to update only gradient.

$$w = w - \alpha \cdot (2\lambda w) \qquad (5)$$

Gradient Update—No misclassification

When the model make a mistake i.e. misclassification on the prediction of the class of the data point for performing gradient update we include the loss along with the regularization parameter.

$$w = w + \alpha \cdot (y_i \cdot x_i - 2\lambda w) \qquad (6)$$

Gradient Update—Misclassification

2) Decision Tree Classification – The main idea of a decision tree is to identify the features which contain the most information regarding the target feature and then split the dataset according the values of these features such that the target feature values are as pure as possible at the resulting nodes. The most informative feature separates the uncertainty from information about the target feature. The search process for a most informative feature goes on until we end up with pure leaf nodes. To decide more informative feature in our dataset we have used attribute Gini index.

- Gini Index—The Gini Index is calculated by subtracting the sum of squared probabilities of each class from one. It satisfies larger partitions and easy to implement whereas information gain satisfies smaller partitions with distinct values [12].

$$\text{Gini Index} = 1 - \sum (P(x=k))^2 \qquad (7)$$

To choose a split a feature with low Gini Index is selected. For the construction of decision tree a classic CART algorithm uses Gini Index.

VII IMPLEMENTATION

A. Stage 1 (Data Collection)

To realize a supervised learning algorithm the first requirement is a dataset. Hence the first step towards implementation is data collection. An environment resembling the forest situations at the time of initiation of fire. The data of each node is recorded. After certain weeks, set of CSV file is generated. Detection of forest fire requires the features such as temperature, humidity, smoke etc. For our project, we tried two methods to collect the data. We created dummy dataset by taking some samples at room temperature then by burning the leaves and finally the samples were taken when the fire was stopped.

B. Stage 2 (Model Generation)

This stage is dedicated to training the agent to generate an accurate and flexible model. The same dataset is divided into two parts. One is used for training purpose whereas the other is used for validation of the model. It uses an Decision tree based approach for the classification purpose.

C. Stage 3 (Nodes Deployment)

All the sensor nodes are deployed over the entire area under surveillance and are launched. Once commenced, they periodically update the data from sensors on the cloud.

D. Stage 4 (Prediction)

At the base station, the updated values are used to predict whether a fire like situation is created. An alarm is generated to alert the fire fighter in case of emergency.

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VIII RESULT

A. SVM Algorithm

The result of SVM algorithm is discussed below:

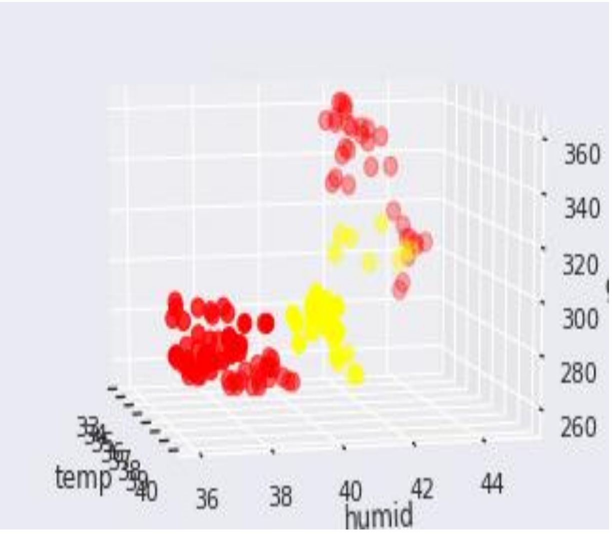

Figure 3 Visualization of Dataset

No Fire

Fire Present

The classification report generated by the SVM algorithm gives an idea about accuracy of the algorithm.

	precision	recall	f1-score	support
0	0.54	0.78	0.64	55
1	0.76	0.51	0.61	73
accuracy			0.62	128
macro avg	0.65	0.64	0.62	128
weighted avg	0.66	0.62	0.62	128

Figure 4 Classification Report for SVM

The accuracy of the model is 62%.

B. Decision Tree Algorithm

The model generated by this algorithm is as follows:

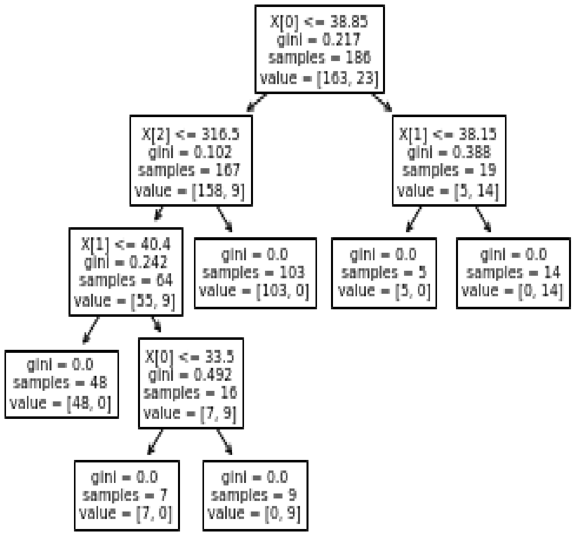

Figure 5 Decision Tree Model

	precision	recall	f1-score	support
0	0.98	1.00	0.99	52
1	1.00	0.96	0.98	28
accuracy			0.99	80
macro avg	0.99	0.98	0.99	80
weighted avg	0.99	0.99	0.99	80

Figure 6 Classification Report for Decision Tree

The decision tree model's accuracy is 99%.

C. Calculations

Parameters calculated to check performance of algorithms

a. Accuracy – Accuracy can tell us immediately whether a model is being trained correctly.

$$Accuracy = \frac{truepositives + truenegatives}{Totalsamples} \quad (8)$$

b. Precision – Precision helps when the costs of false positives are high.

$$Precision = \frac{truepositives}{truepositives + falsenegatives} \quad (9)$$

c. Recall – Recall helps when the cost of false negatives is high.

$$Recall = \frac{truepositives}{truepositives + falsenegatives} \quad (10)$$

d. F1 score – F1 is an overall measure of a model's accuracy that combines precision and recall.

$$F1 = 2 * \frac{precision * recall}{precision + recall} \quad (11)$$

IX PERFORMANCE EVALUATION

In this project, as of now, we have worked with two different machine learning models. We calculated the accuracy of these models. The comparison of these models is as follows:

	SVM	Decision Tree
Accuracy	0.62	0.99
Precision 0	0.54	0.98
Precision 1	0.76	1
Recall 0	0.78	0.99
Recall 1	0.51	0.98

Based on these observations after our experiment and analysis we can clearly compare the performance of the models to predict the chances of fire.

X CONCLUSION

From this project we came to the conclusion that decision tree has a remarkable accuracy of 99% in predicting fires in forest areas. This reduces the chances of false alarm to a great extent.
Our system is able to differentiate various forest fire scenarios, from initial case (no fire) to detection of fire, fairly accurately. It can accurately determine the growth of fire. This will help in early stages of fire detection and help to confine fire to limited areas before much damage occurs. The system will be very effective in preventing occurrence of false alarms. We aim at monitoring the forests without constant human supervision.

XI FUTURE SCOPE

This project carries a broad prospective for future. Moreover it is a need for great research to be done in this field in the coming years. In future, our project can be extended towards finding an efficient way of localization of the fire, gravity of fire, direction of spread, area burnt and many more. In our experiment, the process of simulation of forest fire was done by burning the dried leaves directly. We could come up with ways to make this simulation more close to actual forest fires. Moreover, we can include the region specific meteorological data in the dataset for generating model for prediction. The nodes can be improved by making them efficient enough to have a better sensing distance, resistant to the harsh forest conditions, energy efficient. A focused research can be done in devising ways of forest coverage with the nodes.

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