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# A smart approach for fire prediction under uncertain conditions using machine learning

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**Abstract**
One of the most ubiquitous cause of worldwide deforestation and devastation of wildlife is fire. To control fire and reach the forest area in time is not always possible. Consequently, the level of destruction is often high. Therefore, predicting fires well in time and taking immediate action is of utmost importance. However, traditional fire prediction approaches often fail to detect fire in time. Therefore, a more reliable approach like the Internet of Things (IoT) needs to be adopted. IoT sensors can not only observe the real-time conditions of an area, but it can also predict fire when combined with Machine learning. This paper provides an insight into the use of Machine Learning models towards the occurrence of forest fires. In this context, eight Machine Learning algorithms: Boosted Decision Trees, Decision Forest Classifier, Decision Jungle Classifier, Averaged Perceptron, 2-Class Bayes Point Machine, Local Deep Support Vector Machine (SVM), Logistic Regression and Binary Neural Network model have been implemented. Results suggest that the Boosted decision tree model with the Area Under Curve (AUC) value of 0.78 is the most suitable candidate for a fire prediction model. Based on the results, we propose a novel IoT-based smart Fire prediction system that would consider both meteorological data and images for early fire prediction.

**Keywords** Forest fires · IoT · Boosted decision trees · Machine learning · Predictive systems · Smart environment

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## 1 Introduction

Forest or wildlife fires which might be the after effect of either ecological conditions or human exercises have been a significant natural issue for over a hundred million years now. Natural fires are the result of lightning, extreme droughts, extreme hot and parched weather; sometimes spontaneous combustion of sawdust and dry leaves can likewise be a reason. Global warming, being nature's way of rebuffing humankind, further acts as a catalyst in the rapid increase number of such cases. Human activities prompting forest fires vary from smoking to recreational activities like borne fire. Albeit both natural and human factors lead to the annihilation of wildlife, the effect fluctuates in the two situations. Since human-caused fires are distinguished early, they are controlled well in time for the majority of the cases while natural fires, for the most part, take more time to be seen by the fire authorities and consequently the proportion of the burnt region is higher. Moreover, forest fires not only bring about deforestation and wildlife annihilation, however, it prompts financial and environmental harm in this manner imperilling human lives also.

As of date, a ton of research is being focussed on recognizing and foreseeing woods fires well in time. The early prediction measures varies from Satellite Image Processing to Wireless Sensor Networks to some Prediction models. The capacity to foresee or detect forest fire events beforehand is required to improve present fire the executives' endeavours. Given the unpredictability, powerful computational Machine learning models are required for predicting a forest fire. Past investigations have proposed Machine Learning calculations to outline spatial appropriation of wildfire frequencies [3]. These calculations incorporate Genetic Programming [5], Regression Trees [11], Support Vector Machines [13], Artificial Neural Networks [21], Random Forest [19] and all the more as of late Convolutional Neural Networks [28].

Similarly, the Internet of Things (IoT) is another framework that can be used in fire reconnaissance, fire alarm or disposal given its ability to sense, process and transmit data [9]. Among the numerous application areas of IoT application, environmental monitoring has started gaining more consideration for viable Disaster management. Previous studies have used multiple IoT components for more profound research towards this domain. These structures incorporate Fire location frameworks dependent on Raspberry Pi [10], Arduino-based frameworks [12], frameworks dependent on Wireless Sensor Networks [6, 8].

Considering the requirement for building up an effective Fire detection framework utilizing the ability of IoT sensors and insight of Machine learning [6, 8, 10, 12], this study endeavours to propose a fire detection framework to detect forest fires in time and minimize the damage it may cause. The significant contributions of this study are:

1. We provide an insight into the state-of-the-art techniques of fire prediction based on IoT sensors and Machine learning.
2. We study and compare the performance of 8 Machine learning algorithms on Cortez-Morais dataset [20], which is one of the most popular datasets used for Fire prediction models.
3. Two-class Machine learning algorithms are compared and evaluated based on Precision, Recall, F-score, Accuracy, and Area Under Curve for early fire detection.
4. Based on the analysis of the results obtained by comparing the Machine learning algorithms, we have proposed an IoT based smart system following the Boosted Decision Tree model, for early fire detection.

The following section discusses the related work. Section 3 primarily covers the architecture for the proposed system. Section 4 focusses on the training and classification of the proposed system. Section 5 focusses on the performance evaluation of various classification models and their comparative analysis. Finally, Section 6 summarises the conclusion and future scope of this work.

## 2 Related work

Traditional methods of forest fire prediction included a forest guard manning the boundaries of forest areas; however, this approach was only effective in case of a small area. This further led to the development of a more automated approach. Machine learning algorithms like Support Vector Machine (SVM) and Random forest were used to predict the area burnt by forest fires in [30]. Similarly, a wireless sensor network model based on a ZigBee protocol is proposed for fire detection [25]. George et al. in their work introduced an SVM based fire prediction system [23]. The algorithm considers past weather conditions to predict the risk of fire in a day. In [7] a prediction model for predicting the intensity of forest fires and area burnt based on meteorological factors is introduced. Similarly, the authors designed a Genetic algorithm-based prediction model based on real-time data [1]. The authors used a two-stage model i.e. computational and analytical stage to minimize the possibility of wrong predictions, considering both historical as well as real-time data.

Some of the works have been focussed on a thorough review of the fire detection approaches and technologies used to date. The authors summarised the various means of forest fire detection, introduced to date along with thorough surveys of their techniques [26]. The main focus of this work is Satellite imaging, Optical sensors, Digital cameras and Wireless sensor networks used for detecting forest fires. Similarly, the authors have discussed the role of statistical methods in predicting forest fires taking into consideration the various aspects of fire and the challenges faced while making accurate predictions [4]. The authors described the various sensors used in fire detection systems in [8]. These sensors can predict fire based on fire-related parameters like temperature, smoke, flames and combustible products.

The performance of any Fire detection system is not only dependent on the approach used, but it also relies on the parameters considered and the type of sensors used in the system to study those parameters. The authors developed the OpenMTC communication platform based on IoT and Machine to Machine communication [2]. This work used various sensors to measure the parameters like temperature, humidity level and the concentration of carbon monoxide gas. Air-borne fire sensing using aircraft or drones have paved the way for advanced approaches of fire detection. These systems can either be automated or semi-automated. A thorough study of manned and unmanned airborne fire sensing is done in [17] discussing the state of the art and limitations along with the possible opportunities. The authors have described a hierarchical wireless sensor network for early fire prediction in risk-prone areas [14]. The system integrates the fire- fighting centres, fire simulators, and GIS systems. The system has central and sensor nodes for monitoring and enabling communication between the sensors and for sensing the real-time environmental conditions respectively. Table 1 depicts a comparison of some of the commonly used fire prediction techniques, based on the literature studied.

**Table 1** Comparison of Fire Prediction Techniques

| Parameter | Forest guard | Satellite Imaging | Wireless Sensor networks |
|---|---|---|---|
| Cost | Low | Very high | Medium |
| Efficiency | Low | Medium | High |
| Accuracy | Low | Medium | High |
| False alarms | Low | Low | Medium |
| Delay | Long | Too long | Small |
| Information about fire behaviour | Yes/ No | Yes | Yes |

## 3 Proposed architecture

The proposed framework aims to analyse the images of the forest area and detect different parameters like temperature, relative humidity, and Carbon Mono-oxide (CO) level concurrently and persistently throughout the day. The two outputs will at that point be combined to acquire the condition of the forest area further ordering it into the instance of Fire and No Fire utilizing the Boosted Decision Tree characterization model. Figure 1 depicts a practical review of the proposed framework.

As depicted in Fig. 1, we will be considering not just the readings as observed by multiple sensors, but the image of the forest area would also be considered to achieve more accurate results. The advantage of adopting this hybrid model is two-fold: a) since the decision-making is based on the physiological data along with the images, the chances of false alarm will be minimised to almost negligible and, b) even if either of the two fail to work, the performance of the system would not be compromised and it would switch to hot-standby mode with a weight 1. For training the proposed model two standardised datasets are being used, as discussed in Section 4.

### 3.1 Detecting fire based on the image of the area

There are few frameworks dependent on satellite image processing [15], even though they are not utilized often in light of the significant expense and poor resolution. There are some frameworks which are dependent on thermal, infrared and optical images [16]. For the proposed framework, an advanced camera would be deployed at the field that would constantly capture images of the forest area. The captured images would be compared with those in the trained dataset available and decisions concerning the fire, or no fire condition would be made.

### 3.2 Sensors for temperature, relative humidity, and CO level

The key to any successful fire detection system lies in its capability to detect a fire as early as possible, preferably before it goes out of control, without creating false alarms. Various sensors are employed in commercial fire detection frameworks; however, no single sensor can be sufficient given the fact that the parameters of fire fluctuate over varied environmental conditions [27, 29]. Therefore, sensors should be deployed in combination for observing two or more parameters. For the proposed system, three sensors would be deployed to measure the temperature, relative humidity and CO level in the atmosphere.

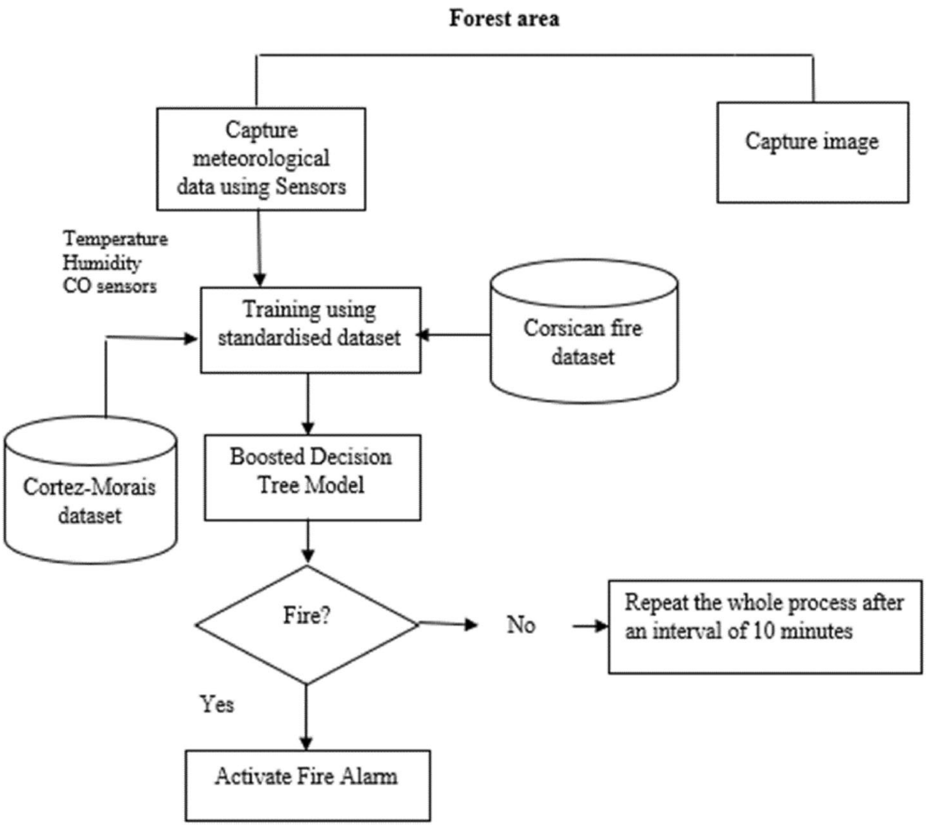


**Fig. 1** Flowchart of the proposed system

### 3.3 Boosted decision tree

A boosted decision tree is an ensemble learning process wherein the subsequent tree amends the miscalculation of the first tree, the third tree amends the miscalculation of the first and second trees, and so forth. It is a method of consolidating multiple weak learners (trees) to obtain a strong classifier [24, 27]. The authors deployed three machine learning models: Boosted regression tree, generalized additive model and Random forest model, to perceive general factors that influence forest fire and compare forest fire vulnerability in the Minudasht Township, Golestan Province, Iran [22]. The outcomes indicated that the Boosted regression model has the most note-worthy value of Area under the curve and hence most reliable amongst the other two models. The final output obtained after multiple iterations are given as in Eq. 1. A similar concept of work was performed in Structured Relevance feature learning Network (SRNet) where the performance of multiple algorithms was evaluated to consider their productivity in representing the global and local framework information of human skeleton joints [20].

$$y\ (x) = \sum t\ wt\ ht\ (x) \tag{1}$$

where,

y (x) is the final ensembled output
wt is the relative weight vector of a tree based on its accuracy
h (x) is the output of the tree

**Algorithm: Boosted Decision Tree**

Step 1: Train classifier $T_1$ for M events

Step 2: Train classifier $T_2$ on the misclassified sample by $T_1$

Step 3: Construct a new classifier $T_3$ for the misclassified values of $T_1$ and $T_2$

Output: Boosted classifier 1

Step 4: Repeat till $M^{th}$ iteration, M= 1, 2……...100.

**Pseudocode: Boosted Decision Tree**

Let the training sample be $T_S$ and M be the number of events. (s= 1,2,3………., m)

Then for an event $k^{th}$,

Initialise $T_1$ (for s=1)

Train classifier $T_1$

Assign weight vector $w_t$ to $T_1$

(higher the misclassification value, the higher weight vector would be assigned to the sample)

Repeat till sample $T_s$

Output: f ($T_1$………. Ts)

**Case 1- No Fire** Consider that the normal temperature is 'T', with relative humidity 'H' and CO level 'C' at a certain time interval 'N'. The readings as given in Table 2 are considered as a normal condition for both sensor readings and images under no fire condition. These readings are considered as the reference readings for the system and any variation in these would be sensed by the installed sensors and the camera by continuous monitoring.

**Case 2 – Fire** Consider that the temperature goes from 'T' to 'T+ t' with relative humidity 'H-h' and CO level 'C + c' at a time interval 'N + n'. In this case, these variations would be observed as the varied weather conditions and decisions would be made as given in Table 2. Simultaneously, the image would also be captured and if the readings for the same variate from the normal conditions, it would be considered as an alarming situation. The system would be designed in such a way that any variation as observed by the system that would be considered alarming, the GPS module would be triggered, and the coordinates of that particular location would be immediately sent to the fire authorities.

**Table 2** Threshold values for the parameters considered

| | Sensor Readings | |
|---|---|---|
| Parameter | | Threshold value |
| Temperature | | 300–500 °C |
| CO level | | 30–75 ppm |
| Relative Humidity | | 30% |
| Image Specifications | | |
| Sequence of Color dominance | | Red > Orange > Yellow > White > Other |

### 3.4 Decision making

The decision-making step plays a vital role in deciding the influence of the image captured and readings observed by the sensors to detect fire. To improve the decision-making process, the analyst may give preferences to both the factors in the form of a weight vector say $\alpha$.

$$\alpha 1 + \alpha 2 = 1, \quad \text{for all } \alpha 1, \quad \alpha 2 \in [0, 1] \tag{2}$$

where,

$\alpha 1$ is the weight vector for readings of the sensors
$\alpha 2$ is the weight vector for images captured

Once the image of the forest area is captured along with the readings for temperature, humidity, and CO level as observed by the sensors, the state of the forest area would be classified into Fire or No-fire scenario. Based on the observations, the required measures would be taken accordingly. Let, $\beta$ be the priority parameter and $\gamma$ be the decision parameter. Table 3 gives the priority list, based on which the decision would be taken. This decision is based on Eq. 3.

$$\alpha 1\ \beta + \alpha 2\ \beta = \gamma \tag{3}$$

## 4 Training and classification

For training the proposed system, two databases would be used. i.e. the fire prediction database by Cortez and Morais and Corsican fire datasets. The Cortez- Morais dataset includes the temporal and spatial components from the Canadian Fire Weather Index (FWI) along with four weather conditions for developing a regression model to predict the burnt forest area [6]. The Corsican fire dataset contains 500 visible images of wildfire gathered from across the world, 100 multi-modal (visible and nearinfrared) images, and 5 sequences of around 30 multi-modal images of outdoor investigational fires [25]. Each image is allied with a black and white (binary) ground-truth picture, annotations, and descriptors. In this work, we will only consider the parameters as given in Table 4.

**Table 3** Priority list for image and sensor readings (based on the study conducted in [18])

| Sensor readings ($\alpha 1$) | |
|---|---|
| Parameter | Priority ($\beta$) |
| Temperature = 400–500 °C, CO level = 50–75 ppm, Relative Humidity < 30% | 3 |
| Temperature = 300–400 °C, CO level = 30–50 ppm, Relative Humidity = 30% | 2 |
| Temperature = 300 °C, CO level ≤ 30 ppm, Relative Humidity ≥ 30% | 1 |
| Images captured ($\alpha 2$) | |
| Red | 3 |
| Orange | 3 |
| Yellow | 2 |
| Other | 1 |

The ability to detect fire based on visual readings and meteorological data varies depending on the area under consideration. Therefore, we assign a weight vector $\alpha$, for sensor readings ($\alpha 1$) and images captured ($\alpha 2$), wherein the assigned priority values for the parameters considered for ($\alpha 1$) and ($\alpha 2$) vary accordingly. The decision parameter $\gamma$ as obtained from Eq. 2, will define the state of the forest area as Fire and No Fire. The sample cases for the same are presented in Table 5.

**Assumption:** $\alpha 1 = \alpha 2 = 0.5$

**Reason** Based on the literature studied, no single technique is enough to detect forest fires. However, combining multiple approaches to study two or more parameters leading to forest fire is more promising. The data readings as observed by the sensors and the images captured by the camera are being considered to be equally crucial in the decision-making process. Therefore, we assign equal weightage to both the aspects considered, with varying priorities as suited.

Then using Eq. 3, we will classify the state of the forest into high, medium and low priority risk. Table 6 shows the classification of risk of forest fire on the decision parameter $\gamma$.

## 5 Result analysis and discussion

To date, various algorithms and systems have been developed to either predict the area that would be burnt during a forest fire or detect hotspots of a forest fire. In this section, we have studied and compared various machine learning algorithms. Eight classification models namely, Boosted Decision Trees, Decision Forest Classifier, Decision Jungle Classifier, Averaged Perceptron, 2-Class Bayes Point Machine, Local Deep SVM, Logistic Regression and Binary Neural Network model have been implemented on the Cortez-Morais dataset containing 517 instances and 13 attributes. The evaluation of the algorithms has been done based on precision, recall, f-score, accuracy and Area Under Curve (AUC). The implementation is done on Microsoft Azure Machine Learning Studio. To test the performance of the algorithms, we used the same dataset as used for training purpose in 70–30 ratio, where 70% data was used for training the model while the remaining 30% data was used for testing purpose.

**Table 4** Summary of the dataset considered

| | |
|---|---|
| Cortez- Morais Dataset | |
| No. of Instances | 517 |
| No. of attributes | 13 |
| No. of attributes taken for this study | 2<br>(Temperature, Relative humidity) |
| Corsican fire dataset | |
| No. of Images | 500 |
| Format | Png |
| Fire Descriptors | 7 |
| Fire Pixels | {Red, Orange, other}- Smoke/ No smoke<br>White – Smoke,<br>Yellow – No smoke |
| Non-fire Pixels | Low, Medium and High intensity |

**Table 5** Summary of sample cases

| Sensor readings | | Images captured | | Decision |
|---|---|---|---|---|
| (α1) | (β) | (α1) | (β) | (γ) |
| 0.5 | 3 | 0.5 | 3 | 3 |
| 0.5 | 3 | 0.5 | 1 | 2 |
| 0.5 | 2 | 0.5 | 3 | 2.5 |
| 0.5 | 2 | 0.5 | 1 | 1.5 |
| 0.5 | 2 | 0.5 | 2 | 2 |
| 0.5 | 1 | 0.5 | 1 | 1 |

## 5.1 Definitions

True positive (tp) = number of instances correctly predicted as fire
False positive (fp) = number of instances incorrectly predicted as fire
True negative (tn) = number of instances correctly predicted as no- fire
False negative (fn) = number of instances incorrectly predicted as no- fire

### 5.1.1 Precision

Is referred to as the gauge of goodness. It answers the question: Of all the instances labelled as fire, how many times it was true? It can be calculated as given in 4:

$$\text{Precision} = \frac{tp}{tp + fp} \tag{4}$$

### 5.1.2 Recall

Is referred to as the gauge of completeness. It answers the question: Of all the predictions of fire that were true, how many did we label? It can be calculated as given in 5:

$$\text{Recall} = \frac{tp}{tp + fn} \tag{5}$$

### 5.1.3 F-score

Is the weighted average of Precision and Recall. Hence, this score considers both false positives and false negatives. It can be calculated as given in 6:

$$\text{F}-\text{score} = 2*\frac{precision*recall}{precision + recall} \tag{6}$$

**Table 6** Classification of risk based on the decision parameter

| γ | Risk |
|---|---|
| ≥ 2 | High priority risk |
| 1.5–2 | Medium priority risk |
| < 1.5 | Low priority risk |

**Table 7** Results

| Algorithm | Precision | Recall | F-score | Accuracy | AUC |
|---|---|---|---|---|---|
| Boosted Decision Trees | 76% | 76% | 76% | 72% | 0.787302 |
| Decision Forest Classifier | 75% | 71% | 73% | 69% | 0.753968 |
| Decision Jungle Classifier | 70% | 80% | 75% | 69% | 0.752381 |
| Averaged Perceptron | 67% | 90% | 77% | 69% | 0.634921 |
| 2 Class Bayes Point Machine | 60% | 80% | 69% | 58% | 0.514286 |
| Local Deep SVM | 81% | 61% | 70% | 69% | 0.68254 |
| Logistic Regression | 60% | 100% | 75% | 69% | 0.749226 |
| Binary Neural Network | 60% | 70% | 64% | 63% | 0.69969 |

### 5.1.4 Accuracy

Is a ratio of fittingly predicted observation to the total observations. The accuracy of an algorithm is its capability to differentiate the fire and no-fire cases correctly. Accuracy of a system can be measured as given in 7:

$$\text{Accuracy} = \frac{\text{tp} + \text{tn}}{\text{tp} + \text{tn} + \text{fp} + \text{fn}} \tag{7}$$

### 5.1.5 AUC

Specifies how much a model is proficient at distinguishing between classes. Greater the value of AUC, better the model. Higher the AUC, better the model is at distinguishing between fire and no- fire cases.

The results obtained after applying the afore-mentioned algorithms on the dataset, are tabulated in Table 7 below:

From Table 7, it can be observed that Local Deep SVM has the highest precision rate of 81% while Logistic regression has the highest recall rate of 100%. But in the case of F-score, the best performer is Averaged perceptron with 77% value of F-score followed by Boosted algorithm and Logistic regression having 76% and 75% F-score respectively. Further, accuracy is highest for Boosted Decision trees. Figures 2 and 3

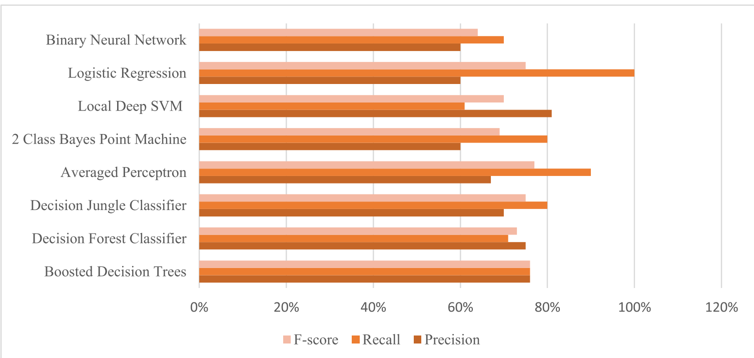


**Fig. 2** Comparative analysis on the basis of precision, recall and F-score

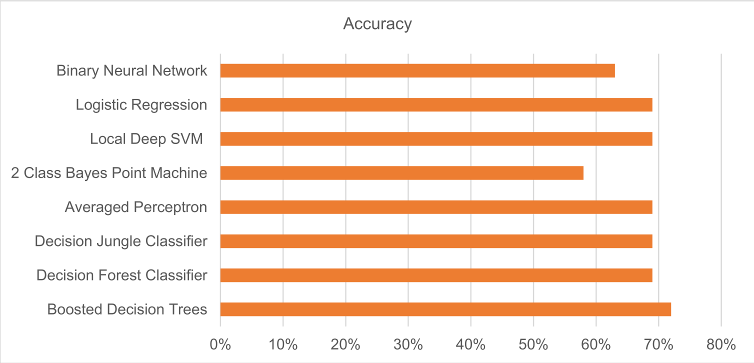


**Fig. 3** Comparative analysis on the basis of accuracy

depicts and compares the performance of the used algorithms in terms of Precision, recall, f-score, and accuracy respectively.

However, based on the readings, it is observed that no single algorithm performs consistently for precision, recall, f-score, and accuracy respectively. Therefore, another evaluation parameter called AUC is considered to quantify the models and find the one with the best performance. The value of AUC falls between 0 and 1, where a higher number indicates better classification performance. Figure 4 depicts the performance of the algorithms based on AUC value.

From Fig. 4, it can be observed that Boosted Decision Tree has the highest value of AUC (0.787) as compared to the rest of the algorithms. Since AUC is a measure of the overall performance of a classification model, we have selected a Boosted Decision Tree model for the proposed work. It can be observed from Table 4 that authors have worked on either machine learning techniques or IoT sensors/devices, but the proposed scheme considers image processing along with the machine learning approach. It is beneficial in terms of accuracy, reliability, and AUC. The existing systems for fire detection are giving accuracy approximately 69% but the proposed system is giving an accuracy of 72% which can be further enhanced by the inclusion of graphical view of the real scenarios of fire. Table 8 gives an overview of existing Fire prediction systems.

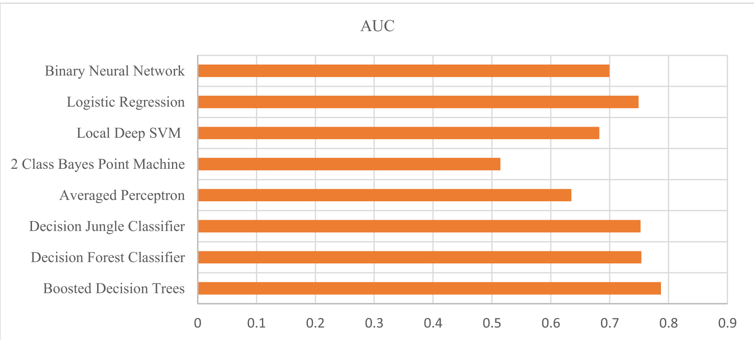


**Fig. 4** Comparative analysis on the basis of AUC

**Table 8** Existing systems

| System | Parameters | IoT sensors/ Devices | Machine Learning algorithm | Image Processing |
|---|---|---|---|---|
| [11] | Temperature, Humidity, Carbon dioxide | – | Regression | – |
| [10] | Light, Gas | Raspberry Pi, Arduino Mega | – | – |
| [6] | Carbon monoxide, Temperature, Humidity | Arduino | – | – |
| [25] | Temperature, Humidity | Wireless Sensor Network | – | – |
| [23] | Temperature, Humidity, Wind Speed | – | Support Vector Machine | – |
| [1] | – | – | Genetic Algorithm | – |
| Proposed system | Temperature, Humidity, Carbon monoxide level | Optical sensors, Humidity sensors, CO sensors, Photodetectors | Boosted Decision Tree | ✓ |

## 6 Conclusion and future scope

In this work, we have studied and compared the performance of eight machine learning models namely, Boosted Decision Trees, Decision Forest Classifier, Decision Jungle Classifier, Averaged Perceptron, 2-Class Bayes Point Machine, Local Deep SVM, Logistic Regression, and Binary Neural Network on the Cortez- Morais dataset containing 517 instances and 13 attributes. The evaluation of the algorithms has been done based on precision, recall, f-score, accuracy and AUC in Microsoft Azure Machine Learning Studio. From the results, it was observed that Boosted Decision trees performed the best in terms of both accuracy and AUC. Therefore, we intend to use Boosted Decision trees for the proposed Fire prediction system. Boosted Decision Tree has 72% accuracy, which is 6% higher than the Neural network model, 14% higher than 2 Class Bayes machine and 3% higher than the remaining 5 algorithms. In terms of AUC, Boosted Decision Trees again performed the best with 0.787 AUC value as compared to 0.75 AUC in case of Decision forest and Decision jungle classifier, followed by 0.69 in Binary Neural network, 0.68 in Support vector machine, 0.63 in Averaged Perceptron and 2-class Bayes point machine performed the worst with only 0.51 AUC. The advantage of the proposed approach is real-time data collection along with low cost as compared to other systems.

In the future, we will consider data gathered in the form of digital images and readings of the meteorological data, as observed by the installed sensors and finally combining the results of both to predict fire. As per the literature review, the presented approach is novel for predicting the occurrence of fire using both meteorological and image-based data. Further experimental research is required once the system is deployed in real-time. However, the proposed model is still quite useful to improve the present firefighting resource management. Moreover, this work opens a promising room for the development of automatic fire detection tools. Although we intend to test the proposed approach in coming future using a real-time learning environment to obtain feedback from the fire-fighting authorities, a lack of data from over different parts of the globe poses a huge research challenge for us.

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