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Early Indoor Fire Prediction Model Using Indoor Laboratory Datasets Based on Machine Learning Classifiers

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ABSTRACT

Indoor fires can have devastating consequences, highlighting the importance of developing effective alarm systems for early fire detection and suppression. This paper proposes a new machine-learning model for indoor fire detection using an indoor fire dataset. The dataset contains information on Humidity, Temperature, Freon Halogen Gas Sensor Module, Total Volatile Organic Compounds, and Estimated Concentration of Carbon Dioxide measures while various indoor materials, such as carton, clothing, and electrical fires of a closed room. It has been observed that commercial fire alarms often do not give early warnings and causing significant damage to the properties. Using decision tree-based algorithms, the proposed model can distinguish between fire, no fire, and fire but no alarm conditions. Experimental results show that the Random Forest-based model can identify these conditions with 99.66% accuracy and 99.64% F_1_score. The outcome of this paper will contribute to the development of smart indoor-fire alarm systems with early-warning capability.

Keywords - **Indoor fire detection, Machine learning application, Smart fire alarms, Ensemble learning.**

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1. INTRODUCTION

Indoor fires can cause significant damage to property and provide a threat to human life if not detected and extinguished in a timely manner. Inventors have been trying to design fire alarms for different circumstances. Channing and Farmer invented the fire alarm system in 1852 [1]. It was manual and used to take a long time to alert people after the fire had started. Four decades later, Francis Robbins Upton first invented the electric fire alarm system in 1890. Smoke detectors are the primary mechanism used by modern fire alarms. The first home smoke detector was invented by Peterson and Pearsall in 1965 [2]. Now-a-days smoke detectors and fire alarms are widely used to alert occupants and authorities of the presence of a fire, but they may not always provide sufficient warning, particularly in large or complex buildings. Smoldering is a type of combustion that occurs slowly and without visible flames. Unfortunately, it is a common cause of residential fires. This process is often triggered by sources of heat such as cigarettes, coal, or electrical malfunctions, which can ignite flammable materials like furniture, cloth, and paper-based products. Smoldering may not be detected by photoelectric smoke detectors or fire alarms until significant damage has already occurred. This has led researchers to explore alternative methods of early detection and prediction, such as machine learning (ML) models. To address this problem, researchers have turned to ML models as a potential solution for early detection and prediction of indoor fires. ML models have shown great potential in predictive analytics. In recent years, researchers have applied ML techniques to fire detection and prediction, particularly for indoor environments. One of the primary challenges in this area is the lack of large-scale and diverse datasets of indoor fires, which are necessary for training and evaluating ML models. Despite the limitations, researchers have been able to develop and test ML models for early indoor fire prediction.

In this paper, we have proposed a ML model for early indoor fire prediction. We work with an indoor fire dataset, which consists of the value of Humidity, Temperature, Freon Halogen Gas Sensor Module (MQ139), Total Volatile Organic Compounds (TVOC), and Estimated Concentration of Carbon Dioxide (eCO_2) for indoor fire materials such as carton, clothing, and electrical materials. We discuss the dataset and preprocessing steps, including data cleaning and feature engineering, and present the model architecture, which includes various ML algorithms, such as Random Forest (RF), LightGBM (LGBM) and Extra Trees (ET). We have evaluated the performance of our model using accuracy, precision, recall and F_1_score. The results demonstrate the effectiveness of our approach and its potential to improve the indoor fire detection and prevention. By using the power of ML and the increasing availability of indoor fire datasets, we believe that our model can make a significant contribution to the field of fire safety and ultimately help to save lives and property.

In addition to ML models, researchers have also explored the integration of Internet of Things (IoT) technologies to enhance indoor fire detection systems. IoT devices, such as smart smoke detectors and sensors, can be deployed throughout a building to collect real-time data on temperature, smoke levels, and other relevant parameters. This data can then be analyzed using ML algorithms to detect patterns and anomalies that may indicate the presence of a fire. The advantage of this approach is the ability to monitor multiple areas simultaneously and provide immediate alerts to both occupants and authorities, improving response time and minimizing potential damage. Another promising avenue of research involves the use of computer vision techniques for fire detection in indoor environments. By analyzing video footage from surveillance cameras or thermal imaging cameras, ML models can be trained to recognize fire-related patterns, such as the appearance of flames or changes in temperature distribution. These models can then be deployed in real-time fire monitoring systems to continuously analyze the visual data and trigger alarms or alerts when a fire is detected. This technology has the potential to overcome the limitations of traditional smoke detectors by providing early detection even in situations where smoke may not be immediately present, such as in the early stages of smoldering fires.

Furthermore, researchers have also explored the integration of ML models with existing fire alarm systems to improve their accuracy and reduce false alarms. By combining data from multiple sources, such as smoke detectors, temperature sensors, and gas sensors, ML models can learn to distinguish between normal environmental variations and genuine fire-related events. This approach can help in reducing the occurrence of false alarms, which can be costly and cause unnecessary panic among occupants. ML algorithms can continuously adapt and update their models based on real-world data, improving their performance over time and enhancing the overall reliability of fire detection systems. Overall, ML models offer a promising solution for early detection and prediction of indoor fires. By leveraging diverse datasets, integrating IoT technologies, exploring computer vision techniques, and improving the integration with existing fire alarm systems, researchers are making significant strides towards enhancing fire safety and minimizing the potential risks posed by indoor fires. Continued research and development in this field hold the potential to save lives, protect property, and create safer environments for all. The objective of this paper is to adopt a ML based model to predict early indoor fire. The rest of this paper is organized as follows: Section II presents some related works about fire detection. Section III describes the methodology along with a brief overview of the datasets and the used classifiers. The experimental results are presented in Section IV together with a thorough analysis and discussion of the main findings. The conclusion of the work and some future directions are provided in Section V, which brings the paper to an end.

2. LITERATURE REVIEW

The following presents a chronological review of research addressing various fires over the past two decades. In 2005, T. Celik, H. Demirel, H. Ozkaramanli, and M. Uyguroglu have developed a real-time fire detector using a color video se-quencing approach [3]. Their method combines collected background scene data with color information to detect fires. They have modeled the adaptive background information using three Gaussian distributions, one for each color channel. The pixel values of the colored data were simulated using these distributions. Their system achieved a detection rate of 98.89%. The next year, D. Stojanova, P. Panov, A. Kobler, S. Džeroski, and K. Taškova have proposed a prediction model for forest fires [4]. The model was built using data from Geographical Information System (GIS), Moderate-resolution Imaging Spectroradiometer (MODIS), and Aire Limitée Adaptation dynamique Développement InterNational (ALADIN). They used different data mining techniques and the result showed that the Decision Trees algorithm gave the best accuracy score (86%). In 2007, M. Hefeeda and M. Bagheri have designed a wireless sensor-based system for the early detecting of forest fires [5]. Y. Liu, Y. Gu, G. Chen, Y. Ji, and J. Li have also investigated on forest fires using a wireless sensor network and proposed a new predicting system for forest fires [6]. They used an artificial neural network architecture to increase the accuracy of prediction. In 2017, A. Solórzano, J. Fonollosa, and S. Marco have researched fire detection using chemical gas sensors [7]. Due to the low cost, they did their experiment on a small-scale setup. They have found that the model trained with the combination of small and large datasets can detect most of the fire cases. For small-scale setups, they found a maximum accuracy of 96%. The main drawback of chemical gas sensors is that sometimes the system responds to non-fire situ-ations and makes false alarms. In the same year, R. Khan, J. Uddin, S. Corraya, J. Kim, R. A. Khan, and J.-M. Kim have proposed a new model to identify color pixels based on RGB for detecting indoor fire, and they got 99.1% accuracy [8]. In 2020, L. Wu, L. Chen, and X. Hao have proposed an early fire warning system based on a neural network using a multi-sensor algorithm based on temperature, smoke, carbon monoxide, and gas sensor readings [9]. They have achieved training accuracy of 99.67%, and the fire detection time was reduced by 32% by the neural network model. Although the research-ers used multiple sensors, they did not use any wireless sensor networks or Internet of Things (IoT) technologies. In 2022, A. Nazir, H. Mosleh, M. Takruri, A. H. Jallad, and H. Alhebsi have conducted IoT-based research on early fire detection in an indoor laboratory environment, focusing on smoldering fires [10]. They have created realistic fires in the laboratory for various flammable items commonly used in the home, (except for oil and gas materials) and collected indoor fire data. Their primary research goal was to determine the sensitivity and detection of indoor smoldering fire cases in var-ious situations. Their proposed dataset can be used to train a ML predictive model for the early detection of indoor fires. In the same year, A. Karouni, B. Daya, and P. Chauvet have worked on forest fire data from the 2012 North Lebanon fire to predict forest fires using decision trees and a neural network [11]. Also, in 2022, M. Mukhiddinov, A. B. Abdusalomov, and J. Cho have proposed an automatic fire detection and notification system for Blind and Visually Impaired (BVI) residents utilizing Convolutional Neural Network (CNN) models and an improved You Only Look Once version 4 (YOLOv4) object detector [12]. They have used a custom indoor fire image da-taset to train the proposed fire detection system. Finally, the authors have found that the improved YOLOv4 model outperformed the traditional YOLOv4 with an average precision of 48.6%.

In short, the development of fire detection systems has been a prominent research area over the last two decades, with various approaches being proposed and tested. These approaches include color video sequencing, prediction models, wireless sensor networks, chemical gas sensors, and ML classifiers. The accuracy of these systems ranged from 86% to 99.67%, depending on the technique used and the dataset employed. While some researchers focused on indoor fire detection, others worked on forest fires or developed systems for the visually impaired. However, false alarms remain a significant challenge for chemical gas sensors and other systems. Future research could focus on addressing this issue and exploring the use of IoT technologies for more robust and accurate fire detection systems. Additionally, the successful application of machine learning classifiers in other domains—such as cyber-attack detection [13], credit card fraud prevention [14], online shopper behavior prediction [15], and test case prioritization in software testing [16]—further supports the potential of ML-based approaches in early indoor fire prediction.

3. RESEARCH METHOD

Early fire detection can reduce the risk of ecological, economical, and social harm in buildings, houses, woods, nuclear power plants, and other public spaces. Despite the fact that there has been a lot of effort done on early fire detection, it remains a difficult problem to solve. Thus, the issue demands the creation of an algorithm that can maximize accuracy while minimizing false alarms. A fire has various characteristics, including light, smoke, heat, gas, and others. While we live in the age of artificial intelligence (AI) and many other ML-based algorithms, we offered a way based on ML methods to provide a better solution for early indoor fire detection. Here we will see a methodological diagram of machine learning process flow at Figure. 1 for indoor fire detection datasets:

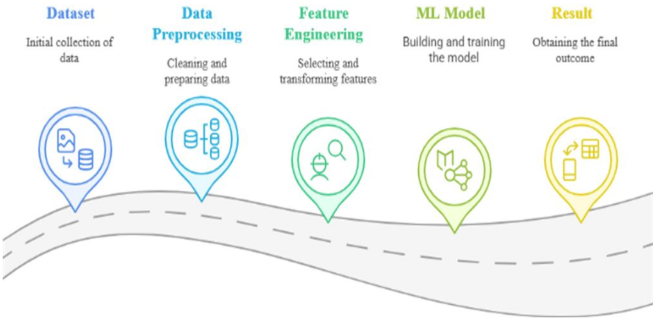

Figure. 1 Machine Learning Process Flow

3.1 Dataset

In this paper, we work with an indoor laboratory fire dataset collected from Mendeley data-base which published by Amril Nazir [17]. This dataset includes time-series data from eight controlled laboratory fire experiments, four of which used electric fire sources, two of which used paperboard carton sources, and the other two of which used clothing sources. The sensor readings of humidity, temperature, MQ139, TVOC, and eCO_2 were recorded for each experiment and data was taken for each second from the point when the flames were first sparked until the point where the fire alarm went off. A unique fire source, such as a carton, electrical, or clothing fire, is represented by a separate Comma Separated Value (CSV) file that contains time-series data. Each CSV files contains Time, Reading ID, Humidity, Temperature, MQ139, TVOC, eCO_2, Detector and Status data. MQ139, TVOC, and eCO_2 are all related to air quality and can be used to measure the presence of certain gases in the air. MQ139 is a type of gas sensor module that can detect and measure the concentration of formaldehyde gas (HCHO) in the air. Formaldehyde is a common indoor air pollutant that can be released by a variety of household products and building materials. MQ139 is part of the MQ series of gas sensors, which are commonly used in air quality monitoring and industrial applications. MQ139 is sensitive to ozone concentrations in the range of 10 to 1000 parts per billion (ppb), and it has a fast response time and low power consumption. TVOC is a measure of the total concentration of all volatile organic compounds in the air. Volatile organic compounds are a broad class of chemicals that can be emitted by a wide range of sources, including cleaning products, paints, adhesives, and building materials. eCO_2 is a measure of the concentration of CO_2 in the air. CO_2 is a common indoor air pollutant that can be generated by human activity, such as breathing, as well as by some household appliances and combustion processes. While MQ139, TVOC, and eCO_2 are measuring different gases in the air, they are all indicators of air quality. High concentrations of any of these gases can indicate poor indoor air quality, which can have negative health effects. It is important to monitor these levels for predicting early indoor fire detection. The detector data shows us if there is any fire or not. Finally, the status data indicate three states, i.e. 0 for no fire, 1 for fire but no alarm and 2 for fire and alarm.

At the below Figure. 2 we can see graphical representation for five sensors data for carton 1. Here at Figure. 2 (a) we have seen the humidity for carton 1 dataset. In the case of carton 1, the humidity remained constant with no fire detected

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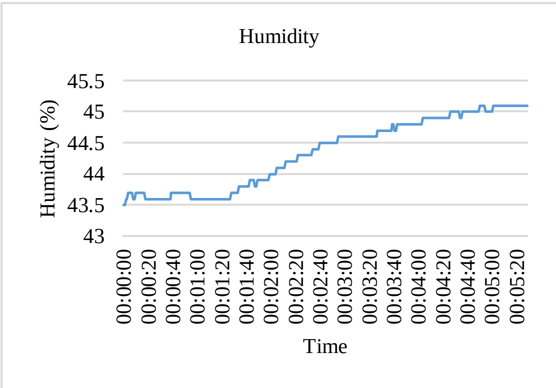
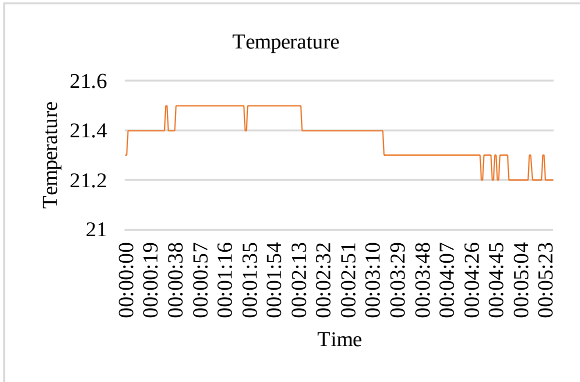
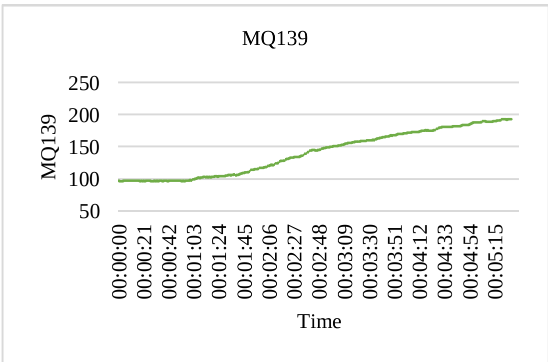
for the first 50 seconds. However, from 51 seconds to 3 minutes and 50 seconds, there was a fire, but the detector failed to detect it. Despite the fire, the humidity only increased slightly to 43.7. It wasn't until 3 minutes and 51 seconds when the humidity finally rose to 44.8 that the detector was able to detect the fire. Graph for Temperature data is represented at Figure. 2 (b) For Carton 1, the temperature remained stable with no fire detected for the first 50 seconds. From 51 seconds to 3 minutes and 50 seconds, there was a fire, but the detector failed to detect it. The temperature only slightly increased to 43.7 degrees Celsius, and it wasn't until 3 minutes and 51 seconds when the temperature rose to 44.8 degrees Celsius that the detector finally detected the fire. Figure. 2 (c) is for MQ139 data graph for carton 1. For Carton 1, at the starting time, the MQ139 sensor recorded a value of 98 with no fire detected. From 51 seconds to 3 minutes and 50 seconds, the sensor recorded a value of 98 with a fire occurring but with no alarm triggered. At 3 minutes and 51 seconds, when the alarm was triggered due to the fire, the sensor recorded a value of 168. Figure. 2 (d) shows the TVOC graph for cartons 1 sample. At time 0:00:00, TVOC value of 0, indicating that there is no fire. At 0:00:51, a fire was present but the alarm does not sound, with TVOC values of 9. At 0:03:51 a fire was detected with an alarm, resulting in significantly higher TVOC values of 2627 for Carton 1. Figure. 2 (e) shows eCO_2 graph for carton 1. When there was no fire, the eCO_2 value remained at a constant 400, with no change over time. However, during a fire, the eCO_2 values increased significantly. During a fire but without an alarm, the eCO2 values varied with values ranging from 400 to 627. The changes occurred at different times with the earliest change occurring at 0:00:13 in the Clothing 1. The earliest increase occurred at 0:03:51 with a value of 4428.



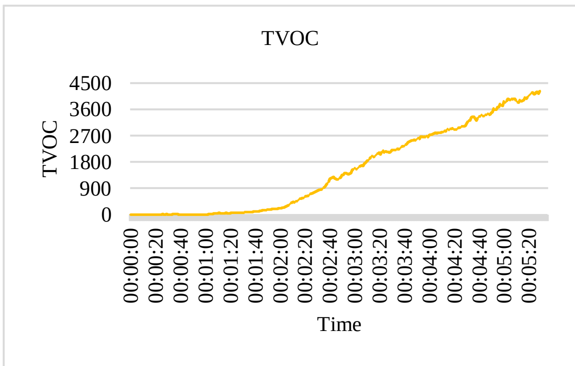
(a)



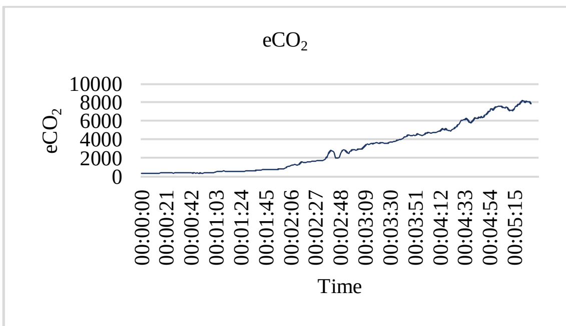
(b)



(c)



(d)



(e)

Figure. 2 Sensor reading of Carton 1 (a) Humidity (b) Temperature (c) MQ139 (d) TVOC (e) eCO_2

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Table 1. representing the data comparison table of our data sets. Table 1. shows readings of various environmental sensors during fire. The sensors include humidity, temperature, MQ139, TVOC, and eCO_2. The readings are provided for three different situations: no fire, fire but no alarm, and fire with alarm. The readings are given for eight different types of fires, labelled as Carton 1, Carton 2, Clothing 1, Clothing 2, Electrical 1, Electrical 2, Electrical 3, and Electrical 4. The time of the readings is also provided for each scenario. These measurements are crucial for ensuring safety in indoor fires and for predicting potential fire hazards.

Table 1. Data comparison

Data Comparison										
			Carton 1	**Carton 2**	**Clothing 1**	**Clothing 2**	**Electrical 1**	**Electrical 2**	**Electrical 3**	**Electrical 4**
Humidity %	No Fire	Time	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	11:50:28	15:06:28
		Value	43.5	61.5	38.7	60.8	38.2	40.7	61.6	61.9
	Fire but No Alarm	Time	0:00:51	0:01:31	0:00:13	0:02:04	0:00:40	0:00:28	12:28:58	15:10:03
		Value	43.7	60.6	39.2	60.4	38.4	38.3	66.1	61.8
	Fire and Alarm	Time	0:03:51	0:06:52	0:06:45	0:19:46	0:37:02	0:32:48	12:34:36	15:48:40
		Value	44.8	60.1	42.5	59.6	41.1	39.3	66.2	63.6
Temperature	No Fire	Time	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	11:50:28	15:06:28
		Value	21.3	24.2	21.8	23.9	21.9	22.7	21.6	23.1
	Fire but No Alarm	Time	0:00:51	0:01:31	0:00:13	0:02:04	0:00:40	0:00:28	12:28:58	15:10:03
		Value	21.5	24.2	21.9	23.9	21.9	22.7	20.9	23.5
	Fire and Alarm	Time	0:03:51	0:06:52	0:06:45	0:19:46	0:37:02	0:32:48	12:34:36	15:48:40
		Value	21.3	24.9	21.6	24.8	22.2	22.9	20.9	24
MQ139	No Fire	Time	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	11:50:28	15:06:28
		Value	98	153	87	114	69	80	81	104
	Fire but No Alarm	Time	0:00:51	0:01:31	0:00:13	0:02:04	0:00:40	0:00:28	12:28:58	15:10:03
		Value	98	173	89	122	69	79	96	107
	Fire and Alarm	Time	0:03:51	0:06:52	0:06:45	0:19:46	0:37:02	0:32:48	12:34:36	15:48:40
		Value	168	361	190	275	120	129	134	245
TVOC	No Fire	Time	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	11:50:28	15:06:28
		Value	0	0	0	0	0	0	0	0
	Fir e but	Time	0:00:51	0:01:31	0:00:13	0:02:04	0:00:40	0:00:28	12:28:58	15:10:03

		Value	9	32	0	39	4	0	105	104
	Fire and Alarm	Time	0:03:51	0:06:52	0:06:45	0:19:46	0:37:02	0:32:48	12:34:36	15:48:40
		Value	2627	1542	1790	2046	5134	5034	1681	5275
eCO_2	No Fire	Time	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	0:00:00	11:50:28	15:06:28
		Value	400	400	400	400	400	400	400	400
	Fire but No Alarm	Time	0:00:51	0:01:31	0:00:13	0:02:04	0:00:40	0:00:28	12:28:58	15:10:03
		Value	400	627	400	584	406	403	442	489
	Fire and Alarm	Time	0:03:51	0:06:52	0:06:45	0:19:46	0:37:02	0:32:48	12:34:36	15:48:40
		Value	4428	7288	6541	6066	4572	7676	2032	6060

3.2 Data Preparation

We worked with eight different time variant datasets which contains five different sensors output. All data are compaced in eight different CSV files according to the unique fire source; i.e. arton 1, carton 2, clothing 1, clothing 2, electrical 1, electrical 2, electrical 3, electrical 4. Every CSV file contains Time, Reading ID, Humidity, Temperature, MQ139, TVOC, eCO_2, Detector and Status. The sampling rate of data collection was one Hz. Here in the CSV files Humidity, Temperature, MQ139, TVOC, eCO_2 are the sensors output data. Detector Indicates wheter there is a fire or not. There are three types of data in the status colum. That are 0, 1 and 2. “0” indicates there is no fire, where “1” is the fire state but when the detector failed to detect the fire and finally “2” indicates fire when the detector successfully identify fire. While preparing data, initially we drop Time, Reading ID and Detector data from each CSV file and merge all the remaining CSV data in one file and found total 11797 data. Further we checked NaN and outliers of the data.

3.3 Classification Method

During our experiment we use total three ML classifier to find best accuracy from different indoor fire detection model. From ML classifier we can see the SHAP value and find confusion matrix. Further, from confusion matrix we have calculated precision, recall, F_1_score and accuracy. All of them are discussed below one by one.

3.3.1. Random Forest Classifier

Random Forest Classifier is a type of ensemble learning algorithm used for classification tasks. It is an extension of the decision tree algorithm, where a set of decision trees are trained on randomly selected subsets of the data and then combined to make predictions. This model can handle complex data and provides feature importance to understand which feature has the most influence over model’s decision.

3.3.2. LightGBM Classifier

"LightGBM" stands for "light gradient-boosting machine" is a machine learning framework that was created by Microsoft. This is also an ensemble model based on gradient boosting. This framework is used for a variety of machine learning tasks, including ranking and classification. It is based on decision tree algorithms and is designed to be both efficient and scalable, which allows it to handle large datasets effectively that have millions of rows and thousands of features. LightGBM is known for its high performance, especially with large datasets.

3.3.3. Extra Trees Classifier

The Extra Trees Classifier is also an ensemble machine learning approach that is similar to Random Forests. It trains multiple decision trees and combines the results to make a prediction. The term "Extra" in Extra Trees stands for "EXTremely RAndomized". Extra Trees uses the entire dataset to train the decision trees. This allows the model to be more robust to noise and outliers in the data. By combining the predictions from multiple decision trees, the Extra Trees Classifier can provide more accurate predictions than a single decision tree.

3.3.4. Feature Importance

During our work we have checked feature importance for three classifiers to identify which feature has the most impact on our model. We get different result for different algorithms. We used SHAP to identify feature importance. SHAP, which stands for SHapley Additive exPlanations [18], [19], [20]. It is a popular and powerful framework for explaining the predictions of machine learning models. SHAP allows us to understand which features are driving the model's output and how much each feature is contributing. This helps us gain insights into how the model makes its predictions and identify potential biases. At Figure. 5 we can see the different impact of feature importance in SHAP value.

3.4 Performance Evaluation Matrics: Confusion Matrix

A confusion matrix is a table that is commonly used to evaluate the performance of a ML algorithm [21], [22]. It is a matrix of actual versus predicted values and is used to determine the accuracy of a model. The confusion matrix contains four categories: (i) True Positives (TP), (ii) False Positives (FP), (iii) True Negatives (TN), and (iv) False

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Negatives (FN). At Figure. 3 we see the confusion matrix for different classifiers.

		Actual	
		Positives (1)	Negatives (0)
Predicted	Positives (1)	TP	FP
	Negatives (0)	FN	TN

Figure. 3 Structure of confusion matrix

3.4.1. True Positives (TP)

TP are one of the four possible outcomes when evaluating a machine learning model's performance. TP refers to the cases where the model correctly identifies a sample as belonging to the positive class. In other words, TP occurs when the model correctly predicts that a positive event has occurred. True positives are an important metric to evaluate a machine learning model's performance, as they measure the model's ability to correctly identify positive instances.

3.4.2. False Positives (FP)

A FP is an error in which a model or classifier incorrectly identifies a negative instance as positive. It occurs when a model predicts a positive outcome for a sample that does not actually possess the target attribute. False positives can lead to inaccurate results and decisions, particularly in applications where false positives can have serious consequences.

3.4.3. True Negatives (TN)

TN occur when a model correctly identifies a sample as not belonging to a certain class, when in fact it does not. In other words, the model accurately classifies a negative instance as negative. This is an important metric in evaluating the performance of machine learning models, particularly in applications where accurate negative predictions are critical. Maximizing the number of true negatives can help to reduce the risk of false positives and improve the overall accuracy and reliability of the model.

3.4.4. False Negatives (FN)

FN refer to the cases where the model makes an incorrect negative prediction by failing to identify a positive instance. This can lead to important instances being missed, particularly in applications where false negatives can have serious consequences, such as in medical diagnoses or fraud detection. Reducing the number of false negatives is an important goal in developing accurate and reliable machine learning models, as it can help to improve the overall performance and effectiveness of the model.
Finally, we have calculated Precision, Recall, F_1_score and Accuracy from Confusion Matrix.

3.5 Precision

Precision also called positive predictive value which is the ratio of True Positives to all the positives predicted by the model [18]. Precision is used in various fields, including machine learning, to measure the degree of exactness or accuracy in a measurement or calculation. In the context of machine learning, precision is an important parameter used to evaluate the performance of a classification model. It allows us to assess how well the model can correctly identify only the relevant instances of a particular class. High precision indicates that the model can minimize false positives and accurately classify instances, making it valuable for applications where precision is critical.

$$\text{Precision} = \frac{TP}{TP + FP}$$

3.6 Recall

Recall is also called as Sensitivity; it is the ratio of True positive to all actual positive of the dataset [23]. Recall is used to evaluate the performance of a model in correctly identifying all relevant instances of a particular class or category, and it is particularly important in applications where missing a relevant instance can have serious consequences.

$$\text{Recall} = \frac{TP}{TP + FN}$$

3.7 F1_score

Combination of Precision and Recall is the F_1_score [22]. F_1_score balance both Precision and Recall in one number. If the F_1_score is 1 then the value is considered as perfect and if it is 0 that indicates the total failure of the model.

$$\text{F1\_score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

3.8 Accuracy

In machine learning, accuracy is used to measure how well a model performs in predicting the correct outcome for a given input [21]. It is calculated as the number of correct predictions divided by the total number of predictions. A high accuracy score indicates that the model is making accurate predictions, while a low score indicates that the model is making more mistakes.

4. RESULTS AND DISCUSSION

In this paper we work with a dataset of three types of indoor fires; in which two cartons, two clothing and four electrical fire data included. We use Google colab for python programming. We work with three different ML classifiers and calculated confusion matrix for each classifier using Google colab. We have also calculated feature importance and shown SHAP value by the help of Google colab. Initially, we used a train-test split ratio of 3:1 (i.e., 75% for training and 25% for testing) to obtain our result. At the below Figure. 4 we have seen the confusion matrix for RF, LGBM and ET Classifiers. The confusion matrix for RF Classifier is shown in Figure. 4 (a) where we see that there is no fire for 706 times, fire but no alarm is 1660 times and alarm is 572 times.

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Whereas for LGBM and ET Classifier at Figure. 4 (b) and Figure. 4 (c) we seen that for both cases there is no fire for 704 times, fire but no alarm is 1659 times and alarm is 573 times. From these confusion matrixes we calculated precision, recall, F_1_score and accuracy for every classifier.

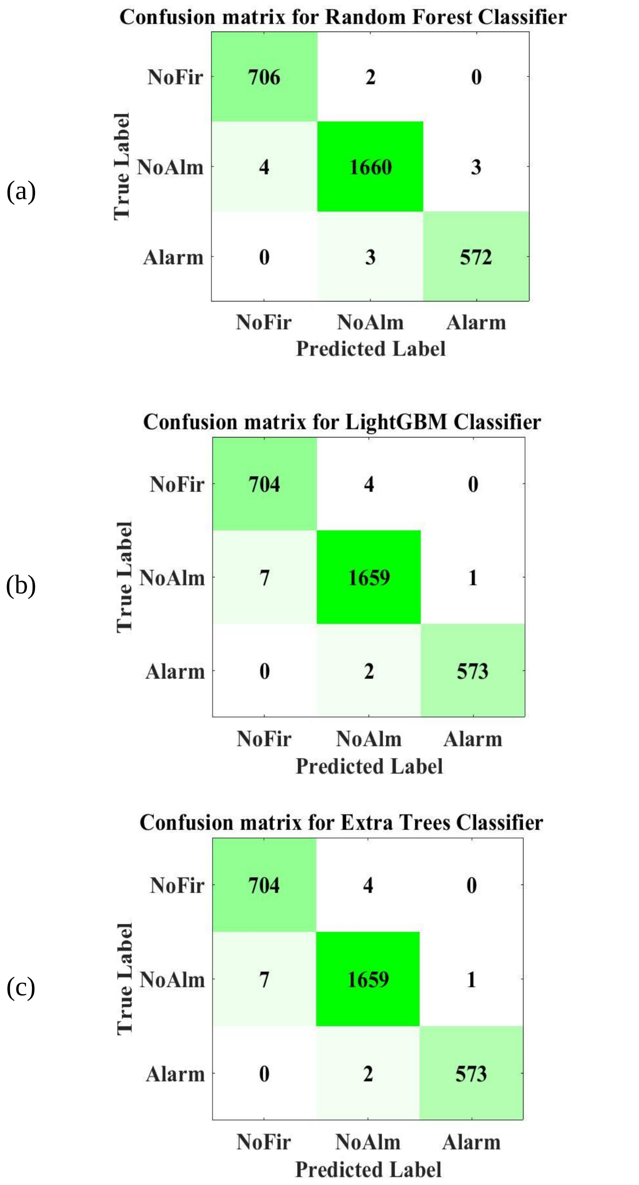

Figure. 4 Confusion Matrix (75:25) for (a) Random Forest Classifier (b) LightGBM Classifier (c) Extra Trees Classifier

At below Figure. 5 we can see the feature importance value in SHAP form and can easily understand the situation when the alarm trigger on or off for different feature values for different classifiers. In Figure. 5 (a), we can see SHAP values for RF Classifier and we see that TVOC and eCO_2 has the most impact for RF Classifier. From Figure. 5 (b) we can easily understand that, for LGBM Classifier TVOC is the most important feature for occurring fire. Using the SHAP value for ET Classifier MQ139 and TVOC are the most important features which is shown in Figure. 5 (c). Overall, TVOC has the most impact for conducting an indoor fire. At Figure. 5 we see the graph has three color marking, whereas the purple color indicates that there is no fire, the blue color indicates that the indoor fire has started but the detectors failed to detect. And finally, the green color indicates that the indoor fire is occurred and the detectors successfully detects fires and started alarming. After that at Table 2. we have seen feature importance values for different classifiers. From the table we can see that the feature importance is different for different classifiers. For RF classifier we get best feature importance value for eCO_2 and second-best value is TVOC, whereas TVOC is best for LGBM when eCO_2 is the second and finally Temperature is the best value for ET classifier when the value for MQ139 and TVOC are close to best value.

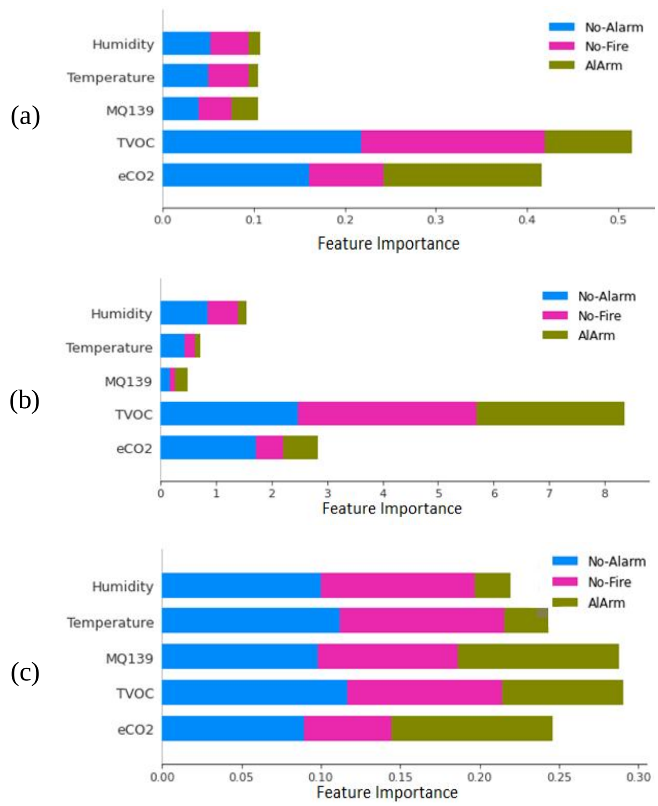

Figure. 5 SHAP Values for different classifiers (a) RF Classifier (b) LGBM Classifier (c) ET Classifier

Table 2. Feature importance of different classifier

Classifier Name	Feature Importance				
	Humidity	Temperature	MQ139	TVOC	eCO_2
RF	0.065	0.097	0.098	0.366	**0.374**
LGBM	0.216	0.094	0.145	**0.290**	0.255
ET	0.156	**0.219**	0.218	0.215	0.191

Further we have calculated the Precision, Recall, F_1_score and Accuracy from confusion matrix. Here we are mentioning the Precision, Recall and F_1_score at No Fire, No Alarm & Alarm conditions for different classifiers at Table 3. where train-test split ratio was 3:1. The notations 0, 1 and 2 indicates that no fire, fire but no alarm and alarm conditions. At Table 3, for Precision we can see that RF Classifier shows the best result at No Fire (0.9944) and No Alarm (0.9970) situation. Whereas LGBM and ET Classifier both indicates the best result for Alarm (0.9983) condition. After that for Recall and F_1_score at No Fire and No Alarm condition RF Classifier provides us best result. Where LGBM and ET

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Classifiers both indicates the best value for Recall and F_1_score at Alarm conditions.

Table 3. Precision, Recall and F_1_score values for different classifiers at 75:25 train-test split ratio

Classifier		RF	LGBM	ET
Precision	No Fire (0)	**0.9944**	0.9902	0.9902
	No Alarm (1)	**0.997**	0.9964	0.9964
	Alarm (2)	0.9948	**0.9983**	**0.9983**
Recall	No Fire (0)	**0.9972**	0.9944	0.9944
	No Alarm (1)	**0.9958**	0.9952	0.9952
	Alarm (2)	0.9948	**0.9965**	**0.9965**
F_1_score	No Fire (0)	**0.9958**	0.9922	0.9922
	No Alarm (1)	**0.9964**	0.9958	0.9958
	Alarm (2)	0.9948	**0.9974**	**0.9974**

When we calculate average values for Precision, Recall, F_1_score and Accuracy for RF, LGBM and ET Classifier at 75:25 train-test split ratio we found that every time RF provides the best results which is shown in Table 4. Form Table 4. we can easily understand that all the value for RF Classifier gives the best result. We get best average Accuracy for RF Classifier and the Accuracy is 99.59%. That means the system which is designed with RF Classifier can predict early fire 99.59% times accurate. Also, we have calculated the average F_1_score and Accuracy for two best features (TVOC and eCO_2) data for three different classifiers at 75:25 train-test split ratio and also shown at the same table. For average best features ET provide us the best F_1_score (96.81%) whereas RF provides the best Accuracy (96.59%) among two best feature importance average values. While we compare the average of five features values and best features value, we see that the Accuracy for five features value is 99.59% and the Accuracy for best features value is 96.59% and we can say that the five featured data provides us the best results.

Table 4. Average values for three classifiers at a glance at 75:25 train-test split ratio

Average		RF	LGBM	ET
All Features	**Precision**	**0.9954**	0.9949	0.9949
	Recall	**0.9959**	0.9954	0.9954
	F_1_score	**0.9957**	0.9951	0.9951
	Accuracy	**0.9959**	0.9953	0.9953
Best Features (TVOC and eCO_2)	**F_1_score**	0.9665	0.9665	**0.9681**
	Accuracy	**0.9659**	0.9648	0.9658

We have also changed our train-test split ratio and calculated for different train-test split ratio to find out the best result. We also train-test our model at 60:40 and 85:15 split ratios and compared our result with 75:25 trained-tested data's which is shown at Table 5. We get best values for RF Classifier rather than LGBM and ET Classifier while calculating Precision, Recall, F_1_score and Accuracy and every time we get best result for 85:15 train-test split ratio. We found the best accuracy for RF Classifier at 85:15 train-test split ratio and the best accuracy is 99.66%.

Table 5. Average values for three classifiers at 75:25, 60:40 and 85:15 train-test split ratio

Train-Test Split Ratio	Classifier	Precision	Recall	F_1_score	Accuracy
75:25	RF	**0.9954**	**0.9959**	**0.9957**	**0.9959**
	LGBM	0.9949	0.9954	0.9951	0.9953
	ET	0.9949	0.9954	0.9951	0.9953
60:40	RF	**0.9938**	**0.9948**	**0.9943**	**0.9947**
	LGBM	0.9923	0.993	0.9926	0.993
	ET	0.9923	0.993	0.9926	0.993
85:15	RF	**0.9967**	**0.9961**	**0.9964**	**0.9966**
	LGBM	0.9949	0.9958	0.9954	0.9955
	ET	0.9949	0.9958	0.9954	0.9955

Now we will compare our result with various previous works on indoor and outdoor fires. Table 6. Shows a comparison between previous works among last two decades and our results. We see that researchers work with different types of fires with various types of datasets. Some of them use video color information data, GIS data or Color pixel based RGB data, while others use chemical gas sensors data or multi sensor data. Researchers got different results based on their methods and datasets. As we see on the Table 6. L. Wu, L. Chen, and X. Hao got 99.67% accuracy for indoor fire using multi sensor data in 2020. Using Color pixel based on RGB data in 2017, R. Khan, J. Uddin, S. Corraya, J. Kim, R. A. Khan, and J.-M. Kim found 99.1% accuracy. In our paper, we use indoor fire dataset and found 99.66% accuracy.

Table 6. Literature review

Author	Category	Dataset	Accuracy
Celik et al. [3]	Indoor and Outdoor Fire	Video color information	98.89%
Stojanova et al. [4]	Forest Fire	GIS, MODIS, ALADIN	86%
Solórzano et al. [7]	Indoor Fire	Chemical gas sensors	96%
Khan et al. [8]	Indoor Fire	Color pixel based on RGB	99.1%
Wu et al. [9]	Indoor Fire	Multi sensor data	99.67%
Mukhiddinov et al. [12]	Indoor Fire	Indoor fire image dataset	73.6%
Our Result	Indoor Fire	Indoor fire	99.66%

In this paper work we have used ML classifiers to identify three types of indoor fires (carton, clothing, and electrical fires). The study used a dataset and three different ML classifiers (RF, LGBM, and ET) to analyze the data. Feature importance values for each classifier were calculated and presented in Table 2. The SHAP values were used to understand the importance of features and how they relate to the alarm trigger on or off. Initially, we have used 75% data for training and 25% data for testing and calculated precision, recall, F_1_score, and accuracy for each classifier. The confusion matrix for each classifier was presented in Figure. 4, and the precision, recall, and F_1_score values were presented in Table 3. We found that RF provides us the best results. Further we took 60:40 and 85:15 train-test split ratio for our ML model. Finally, we found best result (99.66% accuracy) at 85:15 train-test split ratio for RF classifier.

5. CONCLUSION

In this research, we have trained and tested a machine learning model using three different classifiers (RF, LGBM, and ET) on an indoor fire dataset containing carton, clothing, and electrical fire data information for humidity, temperature, MQ139, TVOC, and eCO_2. We used three types training-to-testing ratio (60:40, 75:25, 85:15) and cross-validated the data ten times to evaluate the accuracy, precision, recall, and F_1_score of the classifiers. Our results showed that the RF Classifier achieved the highest accuracy at 99.66% for 85:15 train-test split ratio, making it a promising candidate for the early detection of indoor fires.

For future work, we recommend exploring the use of additional features or sensors in the dataset, as well as testing the model on different indoor environments and fire scenarios. It would also be beneficial to investigate the use of other ML algorithms or combinations of algorithms, to further improve the accuracy and robustness of the model. Overall, our paper demonstrates the potential of ML in early detection of indoor fires, which can help decrease the losses associated with these incidents and improve the safety of indoor environments.

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