PREDICTING FIRE ALARMS USING MULTI SENSOR DATA: A BINARY CLASSIFICATION APPROACH

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ABSTRACT: Fires pose significant threats to human life, property, and the environment. Early detection of fire incidents is crucial to prevent extensive damage and to ensure the safety of occupants. Traditional fire alarm systems typically rely on a single type of sensor, such as smoke detectors or heat sensors, to detect specific fire indicators. These systems operate based on predefined thresholds and triggers. However, they can be prone to false alarms triggered by non-fire-related events (e.g., cooking fumes or dust) and may not provide early warning signs in certain scenarios. To address these limitations, researchers and engineers have turned to advanced technologies, such as multi-sensor data analysis and machine learning algorithms, to develop more reliable and efficient fire alarm prediction systems. On the other hand, the need for a more robust and accurate fire alarm prediction system stems from the shortcomings of traditional methods. False alarms not only lead to wasted resources but also desensitize occupants, potentially leading them to ignore genuine alarms. Additionally, a delayed response to a fire incident can result in severe consequences, making it essential to develop an intelligent system that can effectively and timely predict fire events. Therefore, this work presents the utilization of multi-sensor data and binary classification to develop a more reliable fire alarm prediction system. The experiments are conducted using a dataset collected from various sensor inputs, including air temperature, humidity, CO2 concentration, molecular hydrogen, ethanol gas, and air pressure etc. Then applied binary classification algorithm to learn patterns from the data and classify fire-related events accurately. The results showed promising improvements in prediction accuracy, reduced false alarm rates, and early detection of fire incidents.

Keywords: Fire Alarms, Multi-Sensor Data, Binary Classification Approach, Early Detection, Traditional Fire Alarm Systems, False Alarms, Advanced Technologies, Machine Learning Algorithms, Support Vector Machines, Random Forests, Neural Networks, Reliability, Efficiency, Environmental Conditions, Impending Fire, Sensor Integration.

1. INTRODUCTION

In fire safety, the ability to accurately predict and swiftly respond to potential fire incidents is of important. Traditional fire alarm systems often rely on a single sensor type, limiting their capacity to discern between false alarms and genuine threats. Recognizing the need for more robust and reliable fire detection mechanisms, use of multi-sensor data and employ a binary classification approach for predicting fire alarms. The utilization of multiple sensors, such as smoke detectors, heat sensors, and gas sensors, provides a holistic perspective on environmental conditions and potential fire hazards. The integration of multiple sensors and a binary classification model can potentially revolutionize fire alarm systems, providing a more reliable and efficient solution for fire detection in various settings, including residential, commercial, and industrial environments. The binary classification approach involves training machine learning models to differentiate between normal environmental conditions and those indicative of an impending fire. This method allows for a more advanced analysis of sensor data, enabling the system to make informed decisions and trigger alarms only when genuine threats are detected. The project will explore various machine learning algorithms, including but not limited to support vector machines, random forests, and neural networks, to determine the most effective model for this specific application. Through the implementation of multi-sensor, binary classification approach, we aim to provide a cutting-edge solution for fire alarm systems that not only enhances the reliability of fire detection but also minimizes the occurrence of false alarms. Fire incidents pose a severe threat to human lives, property, and the environment. Despite advancements in fire detection technology, existing systems often exhibit limitations, such as high rates of false alarms and delayed responses. Traditional fire alarm systems relying on single-sensor technologies may struggle to discern between environmental variations and genuine fire emergencies, leading to inefficient use of resources and compromised safety. The problem addressed in this research lies in the need for more accurate and reliable fire alarm systems. The challenge is to develop a system that can effectively discriminate between normal environmental conditions and the early signs of a fire, reducing false alarms and ensuring swift responses in critical situations.

2. LITERATURE SURVEY

2.1 Introduction

Predicting fire alarms using multi sensors presents a significant advancement in fire detection systems, particularly through a binary classification approach. Multi sensor systems combine various types of sensors, such as smoke, heat, and gas detectors, to improve the accuracy and reliability of fire alarm systems. By employing a binary classification approach, the system aims to classify the input data into two categories: alarm and non-alarm conditions. This approach enables the system to effectively discriminate between normal environmental variations and potentially hazardous fire conditions, reducing false alarms while ensuring timely detection of fires. A survey of research in this field reveals various methodologies and techniques employed for binary classification in fire alarm prediction using multi sensors. These methods often involve preprocessing techniques to enhance the quality of sensor data, feature extraction to identify relevant patterns indicative of fire, and machine learning algorithms such as support vector machines, decision trees, or neural networks for classification. Additionally, the survey may highlight challenges such as sensor fusion, environmental variability, and real-time processing requirements, providing insights into ongoing research efforts aimed at improving the robustness and efficiency of multi sensor fire alarm prediction systems.

2.2 Related Work

Vorwerk et.al [1] proposed early fire detection using multi-sensor nodes. The goal was to investigate whether training data from a small-scale setup (source domain) could be used to identify various incipient fire scenarios in their early stages within a full-scale test room (target domain). In a first step, we employed Linear Discriminant Analysis (LDA) to create a new feature space solely based on the source domain data and predicted four different fire types (smoldering wood, smoldering cotton, smoldering cable, and candle fire) in the target domain with a classification rate of up to 69% and a Cohen's Kappa of 0.58. Notably, lower classification performance was observed for sensor node positions close to the wall in the full-scale test room. In a second experiment, we applied the TrAdaBoost algorithm as a common instance transfer technique to adapt the model to the target domain, assuming that sparse information from the target domain was available. Boosting the data from 1% to 30% was utilized for individual sensor node positions in the target domain to adapt the model to the target domain.

Park et.al [2] proposed for IoT-based fire-detection systems to exhibit the requisite reliability, research related to the analysis of detection signals should be actively promoted and conducted. However, there has been no research activity based on actual operational data, apart from the research that has been conducted in laboratory environments. The primary reason for that state of affairs had been that the installation and use of IoT-based fire-detection systems on a large scale has been rare, worldwide. Consequently, with respect to the fire-signal characteristics of IoT-based fire-detection systems, related data in that study were obtained by investigating actual fire accident cases, using fire alarm data that occurred over a period of 5 years. Based on the signal pattern analysis results using those field data, a fuzzy logic system for recognizing fire signal patterns was developed and verified. As a result, in the actual fire accidents examined, an "alarm" condition—corresponding to the high possibility of fire among the five fire alarms—was determined 30 s before the actual fire alarm. Moreover, it was also found that approximately 80% of non-fire alarms could be reduced in the actual fire alarms that occurred at Institute K during the 5-year period examined.

Bandara et.al [3] proposed the changed circumstances of landscapes, vegetation patterns, weather conditions and ecosystems account for the complexity. Therefore, continual attention was essential for the development of bushfire management strategies. In that context, that paper undertook a comprehensive literature review of bushfire management strategies, encompassing aspects such as bushfire prediction, detection, suppression and prevention. Based on the review, a bushfire management framework was proposed that can eliminate or successfully mitigate the consequences of bushfires. Further, the paper delves into the domains of fire weather conditions, the initiation of bushfires and the adverse consequences stemming from those fires. Both terrestrial and aerial remote sensing methods have proven to be effective in predicting and detecting bushfires. Nevertheless, a simple unique solution cannot be proposed for bushfire management. Changing weather conditions, topography and the geographic mix of asset types need to be considered when deciding on bushfire management strategies and their breadth and depth of application.

Wang et.al [4] proposed a article that depicts research from the perspective of a single type of sensor detection. In terms of fire smoke, we select dual-wavelength photoelectric smoke sensors for fire-data collection and a genetic algorithm to optimize the classification and detection of random forest fires. From the perspective of fire CO concentration, we use PSO-LSTM to train a CO concentration compensation model to reduce sensor measurement errors. Research is then conducted from the perspective of various types of sensor detection, using the improved BP-AdaBoost algorithm to train a fire-detection model and achieve the high-precision identification of complex environments and fire situations.

Yijie et.al [5] proposed "smart firefighting" became a popular research topic which aims at improving the efficiency of fire protection and safety. However, in existed smart firefighting systems: (1) state and analog firefighting IoT data was not fully utilized; (2) fire risk assessment required a long time to update; (3) few existed works can recognize faults and forecast potential risks with both temporal and spatial information from multiple IoT sensors. A novel framework was introduced to solve the problems as followed: (1) Short-term Fire Risk Assessment (SFRA) is proposed by considered the working status, maintenance and rectification performance of firefighting facilities based on IoT state data; (2) Prognostics and Health Management (PHM) algorithms are applied in the fire safety field for the first time to detect faults and forecast potential risks with temporal and spatial information with IoT analog data from single or multiple sensors. The case study concluded that the proposed framework extends the utilization of IoT data, improved the efficiency of fire risk assessment and enhanced the accuracy of faults detection and potential risk forecast. Moreover, the deployed firefighting system improved the data privacy and computational efficiency.

Sowah et.al [6] proposed a paper that presented the design and development of a fuzzy logic-based multi sensor fire detection and a web-based notification system with trained convolutional neural networks for both proximity and wide-area fire detection. Until recently, most consumer-grade fire detection systems relied soled on smoke detectors. Those offer limited protection due to the type of fire present and the detection technology at use. To solve that problem, we presented a multi sensor data fusion with convolutional neural network (CNN) fire detection and notification technology. Convolutional Neural Networks are mainstream methods of deep learning due to their ability to perform feature extraction and classification in the same architecture. The system was designed to enable early detection of fire in residential, commercial, and industrial environments by used multiple fire signatures such as flames, smoke, and heat. The incorporation of the convolutional neural networks enabled broader coverage of the area of interest, using visuals from surveillance cameras. With access granted to the web-based system, the fire and rescue crew got notified in real-time with location information. The efficiency of the fire detection and notification system employed by standard fire detectors and the multi sensor remote-based notification approach adopted in that paper showed significant improvements with timely fire detection, alerting, and response time for firefighting. The final experimental and performance evaluation results showed that the accuracy rate of CNN was 94% and that of the fuzzy logic unit is 90%.

Cobian-Iñiguez et.al [7] proposed that resulted in the growth of the wildland urban interface (WUI) where an increased risk to people and their property from fires existed. To better plan for increased WUI fire activity, various initiatives have focused on building and planning practices that decrease the chance of ignition and increase building survivability in the case of a fire. Crucial to understood how to best protect the built environment during a WUI fire is a thorough understood the causes of WUI fire ignition and spread and the factors that lead to building survivability. In that chapter, we described key factors leaded to building ignition, namely ember ignition and direct flame contact, building features shown to enhance building survivability, land management and fuel treatment practices. We use these basic principles of WUI fire behavior to propose the adoption of artificial intelligence and machine learning to tackle the WUI fire safety problem.

Abid et.al [8] proposed forest fires are one of the major environmental concerned, each year millions of hectares are destroyed over the world, caused economic and ecological damage as well as human lives. Thus, predicted such an environmental issue became a critical concern to mitigate that threat. Several technologies and new methods had proposed to predict and detect forest fires. The trend was toward the integration of artificial intelligence to automate the prediction and detection of fire occurrence. That paper presented a comprehensive survey of the machine learning algorithms based on forest fires prediction and detection systems. First, a brief introduction to the forest fire concern was given. Then, various methods and systems in forest fires prediction and detection systems were reviewed. Besided worked that reported fire prediction and detection systems, studied that assessed the factors influenced the fire occurrence and risk are discussed. The main issues and outcomes within each study are presented and discussed.

3. PROPOSED METHODOLOGY

3.1 Overview

Traditional fire alarm systems, crucial for ensuring safety and property protection, encounter challenges such as false alarms and limitations in adapting to dynamic environmental conditions. In response, the integration of Artificial Intelligence (AI) and Machine Learning (ML) automation is pursued to revolutionize fire detection technology. This transformative approach aims to elevate the capabilities of fire alarm systems, fostering accurate prediction while mitigating the occurrence of false alarms.

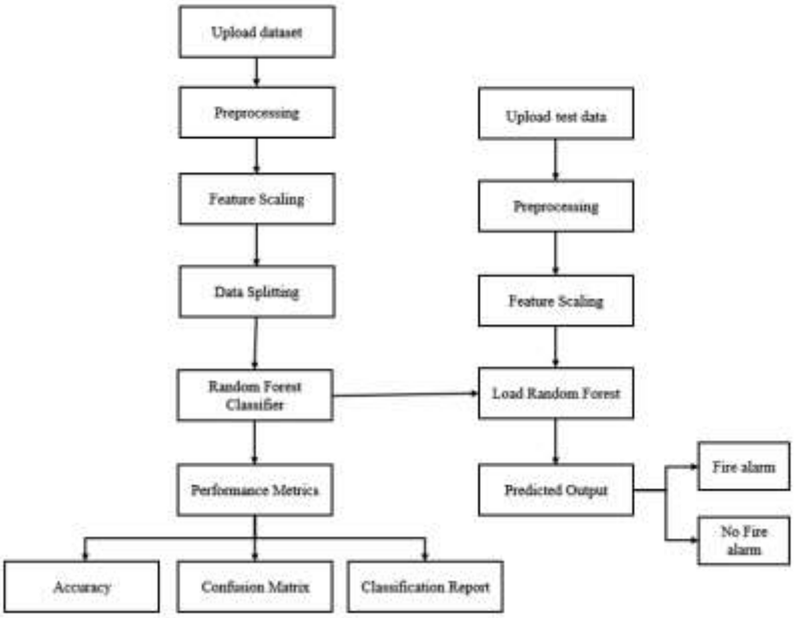

Figure 3.1: Proposed block diagram of Fire alarm prediction

The project ensures seamless integration with existing fire alarm systems, augmenting their capabilities with intelligent features. Additionally, predictive maintenance models are implemented to anticipate sensor calibration or replacement needs, ensuring the continuous reliability of the entire fire alarm system. The project's emphasis on data fusion and integration plays a pivotal role in providing a comprehensive understanding of the environment by combining information from various sensors.

Machine Learning techniques enable efficient feature extraction, identifying key indicators within the sensor data that contribute to a more nuanced comprehension of potential fire events. Anomaly detection models swiftly identify deviations from normal sensor readings, enabling early detection and reducing the likelihood of false alarms triggered by non-fire-related factors. The AI-driven pattern recognition models learn from historical data, facilitating the identification of unique combinations of sensor readings associated with actual fire events. In real-time monitoring, the system continuously analyzes incoming data streams, ensuring a swift response to sudden changes or abnormal patterns that could indicate a fire hazard.

Moreover, the adaptive learning mechanisms employed in the project contribute to the continuous refinement of predictive capabilities. This adaptability allows the system to evolve over time, adjusting to new environmental conditions and accommodating changes in sensor calibration. User feedback becomes a valuable resource in this iterative process, contributing to ongoing improvements in the model's accuracy and adaptability. The seamless integration with existing fire alarm systems not only augments their capabilities but also ensures a smooth transition to the enhanced, intelligent features introduced by the AI and ML components. It also places significant emphasis on reducing false alarms, a common challenge in traditional fire alarm systems, ensuring the continuous reliability of the entire fire alarm system.

3.2 Random Forest Classifier

The adoption of the Random Forest Classifier (RFC) in the project is rooted in its effectiveness and versatility, addressing specific challenges encountered with other classification algorithms, such as the k-Nearest Neighbours (KNN). This section explores the rationale behind choosing the Random Forest Classifier, emphasizing its purpose and advantages within the context of fire alarm prediction using multi-sensor data. Random Forest is a powerful ensemble learning algorithm that leverages the strengths of multiple decision trees to improve classification accuracy and robustness. In the project's context, the transition to Random Forest was motivated by several key factors. Firstly, the inherent complexity of multi-sensor data in fire alarm prediction necessitated an algorithm capable of capturing intricate patterns and relationships within the dataset. Random Forest's ensemble approach, where each decision tree is trained on a different subset of the data and features, facilitates the model of complex interactions present in the sensor readings.

Random Forest has ability to handle high-dimensional feature spaces. In fire alarm prediction, where data from various sensors contributes to the decision-making process, having a classifier capable of efficiently processing and interpreting this diverse information is crucial. Random Forest's capacity to manage a large number of features without overfitting makes it well-suited for the intricate, multi-dimensional nature of the project's dataset.Random Forest is robust against overfitting, a common concern in decision tree-based models. The ensemble nature of Random Forest, which aggregates predictions from multiple trees, mitigates the risk of individual trees memorizing noise in the data. This robustness is particularly valuable in scenarios like fire alarm prediction, where real-world data may contain noise and fluctuations.

Furthermore, Random Forest provides a mechanism for assessing feature importance. This attribute is instrumental in understanding the contribution of each sensor input to the overall predictive performance. By identifying the most influential features, the project gains insights into the critical factors that lead to accurate fire alarm predictions. This interpretability enhances the project's ability to refine the model, optimize sensor configurations, and improve overall system performance.

The purpose of incorporating Random Forest into the project extends beyond achieving 100% accuracy; it involves creating a classification model that is adaptive, robust, and capable of handling the intricacies of multi-sensor data. Random Forest aligns with the project's goal of reducing false alarms, enhancing prediction accuracy, and providing a reliable fire alarm system. Its ability to learn from diverse sources, handle high-dimensional data, and offer insights into feature importance positions it as a strategic choice in the pursuit of excellence in fire alarm prediction using AI and ML automation.

In summary, the integration of the Random Forest Classifier into the project is driven by its adaptability, resilience, and capacity to handle the complexities inherent in multi-sensor data for fire alarm prediction. This strategic choice aligns with the overarching project objective of creating a robust, accurate, and intelligent fire alarm system, setting the stage for improved safety and property protection.

3.3 Advantages

High Accuracy: Random Forest tends to provide high accuracy in classification tasks. By aggregating predictions from multiple decision trees, it reduces the risk of overfitting and generalizes well to new, unseen data.
Robustness: The ensemble nature of Random Forest makes it robust against outliers and noisy data. Individual decision trees may be influenced by noise, but the overall impact is mitigated when combining predictions from multiple trees.
Versatility: Random Forest can be applied to both classification and regression problems. Its adaptability makes it suitable for a wide range of tasks, offering a versatile solution for various machine learning scenarios.
Handles High-Dimensional Data: Random Forest can effectively handle datasets with a large number of features (high-dimensional data). This is particularly useful in applications where the input space includes diverse and numerous variables, such as multi-sensor datasets.
Reduces Overfitting: Individual decision trees are prone to overfitting, capturing noise in the training data. Random Forest mitigates this risk by averaging predictions across multiple trees, providing a more generalized model that performs well on unseen data.
Feature Importance: Random Forest provides a measure of feature importance. This allows users to understand the contribution of each feature to the overall predictive performance. It aids in feature selection, providing insights into which variables are most influential in making accurate predictions.
Efficient Parallel Processing: Random Forest can be parallelized, enabling efficient processing of large datasets. The ability to perform parallel computations makes it suitable for tasks that require handling substantial amounts of data in a time-efficient manner.
Stability and Consistency: The overall stability and consistency of Random Forest contribute to its reliability. The algorithm tends to produce robust results across different runs and is less sensitive to changes in the dataset or hyperparameter settings.
Natural Handling of Missing Values: Random Forest can handle missing values in the dataset without the need for extensive preprocessing. The algorithm naturally accommodates missing data during the training process.
Ensemble Learning Benefits: Being an ensemble learning method, Random Forest benefits from the wisdom of the crowd. Combining predictions from multiple trees helps in reducing biases and errors associated with individual models, leading to a more accurate and reliable overall prediction.
No Need for Feature Scaling: Random Forest does not require feature scaling, making it less sensitive to the scale of input features. This simplifies the preprocessing steps, especially when dealing with diverse types of sensors with different measurement scale

4. RESULTS AND DISCUSSION

4.1 Implementation Description

1. Upload Dataset (): This function opens a file dialog for the user to select a dataset file. It then reads the selected CSV file into a Pandas Data Frame and displays the first few rows of the dataset in the GUI text widgett.

2.preprocess Dataset (): This function preprocesses the dataset by filling any missing values with 0, scales the features using Min-Max scaling, and splits the dataset into training and testing sets using a 80-20 split ratio. It also displays the total number of records in the dataset, the number of records for training, and the number of records for testing. Additionally, it creates a count plot showing the distribution of classes in the dataset.

3.ROC Graph testY, (predict, algorithm): This function plots the Receiver Operating Characteristic (ROC) curve for the given test labels and predicted labels using the recurve function from sklearn. It takes the test labels (testY), predicted labels (predict), and the name of the algorithm as input parameters.

4.Custom_Knn_Classifier(): This function implements a K-Nearest Neighbours (KNN) classifier with a specified number of neighbours (neighbours=10). It computes precision, recall, F1-score, and accuracy metrics for the classifier, plots the ROC curve, and displays the confusion matrix and classification report in the GUI.

5.Random forest classifier (): This function implements a Random Forest classifier using the Random Forest Classifier class from sklearn. It computes precision, recall, F1-score, and accuracy metrics for the classifier, plots the ROC curve, and displays the confusion matrix and classification report in the GUI.

6.Predict (): This function allows the user to select a dataset file for prediction. It uses the trained Random Forest classifier (rf) to predict the classes of the test data and displays the predictions in the GUI.

7.Graph (): This function creates a bar graph comparing the performance (precision, recall, F1-score, and accuracy) of the KNN and Random Forest classifiers.

8.Close (): This function closes the main Tkinter window.

The main part of the script creates a Tkinter window with buttons to upload the dataset, preprocess the dataset, train the KNN and Random Forest classifiers, make predictions, and display performance comparison graphs. It also includes a text widget to display information such as dataset loading, preprocessing results, classifier performance metrics, and prediction results.

4.2 Result and Description

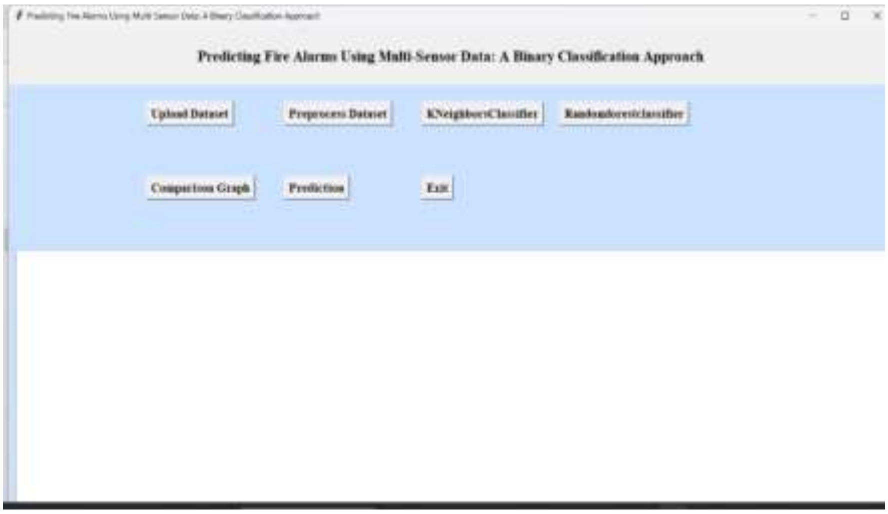

Figure 4.1: Sample UI used for prediction of Fire alarm.

First step is uploading data set. The dataset was collected from a network of multi-sensor systems deployed in various environments prone to fire incidents. The dataset comprises a large collection of samples, each containing readings from multiple sensors. These sensors include smoke detectors, temperature sensors, carbon monoxide detectors, and other environmental sensors. Each sample is associated with metadata such as timestamp, location, and sensor IDs.

Figure 4.2: Sample UI after uploading dataset

Second step is preprocessing the dataset. Prior to uploading, the raw sensor data underwent preprocessing steps to ensure data quality and consistency. This included handling missing values, outliers, and sensor errors. Additionally, feature engineering techniques were applied to extract relevant features from the raw sensor readings, such as temporal patterns, sensor correlations, and statistical features.

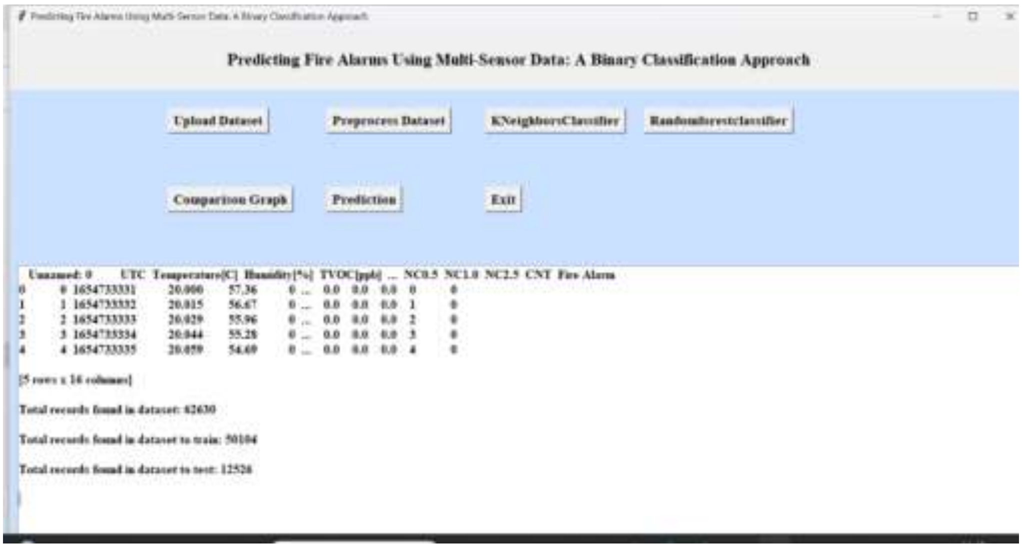

Figure 4.3: Sample UI after Preprocessing dataset

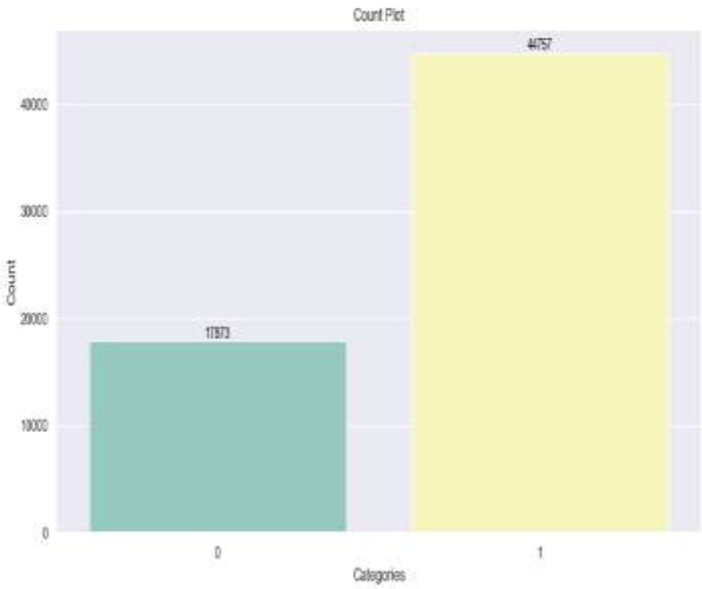

Figure 4.4: Count plot of dataset

From the above graph shows count plot consisting categories of 0 and 1. Here, 0 represents 'Fire' category and 1 represents 'No Fire' category.

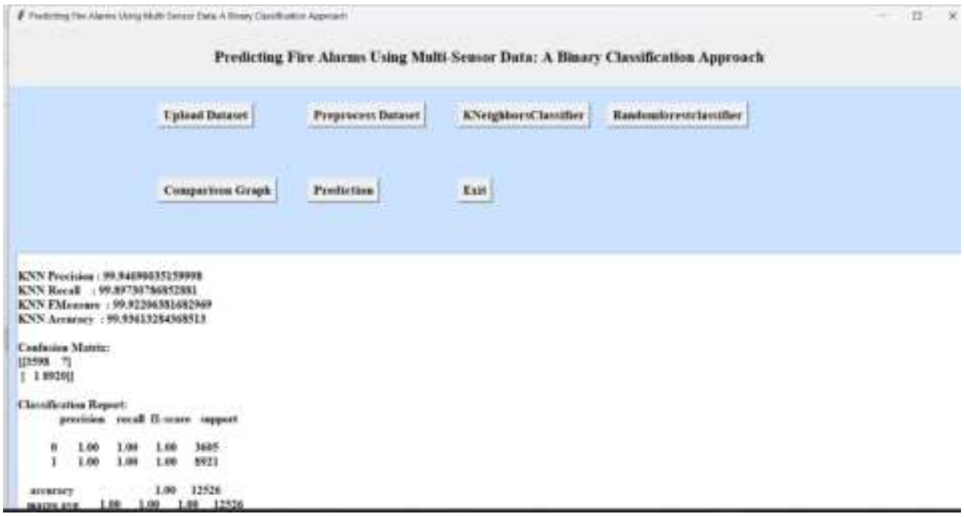

Figure 4.5: Performance evaluation of KNN classifier

When K Neighbour classifier algorithm is used, the above table shows classification report and confusion matrix. In classification report, accuracy, precision, and F1 score metrics give 99% prediction rate. In confusion matrix, false positive values and false negative values are more than one.

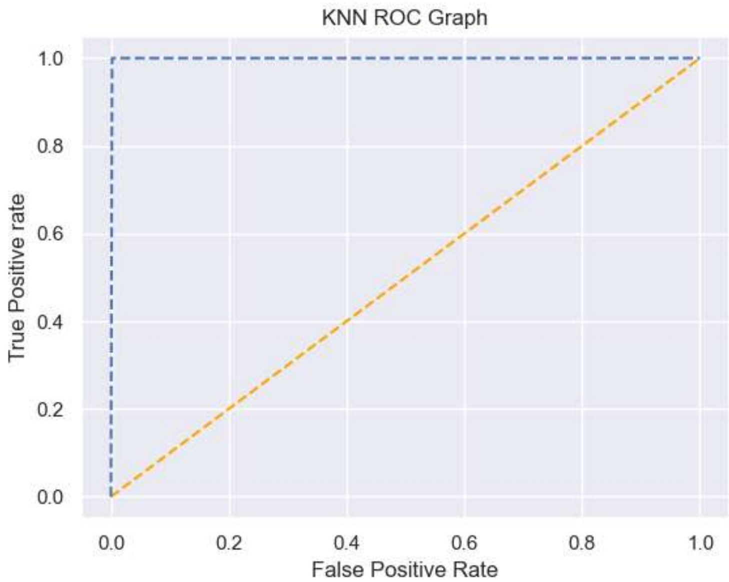

Figure 4.6: ROC Graph for KNN Classifier

The ROC (Receiver Operating Characteristic) graph for the K-Nearest Neighbour's (KNN) classifier plots the true positive rate and the false positive rate at given threshold settings. With the false positive rate on the x-axis and the true positive rate on the y-axis, in this graph a 99% prediction value is achieved. The ROC graph becomes a crucial visualization for evaluating its performance.

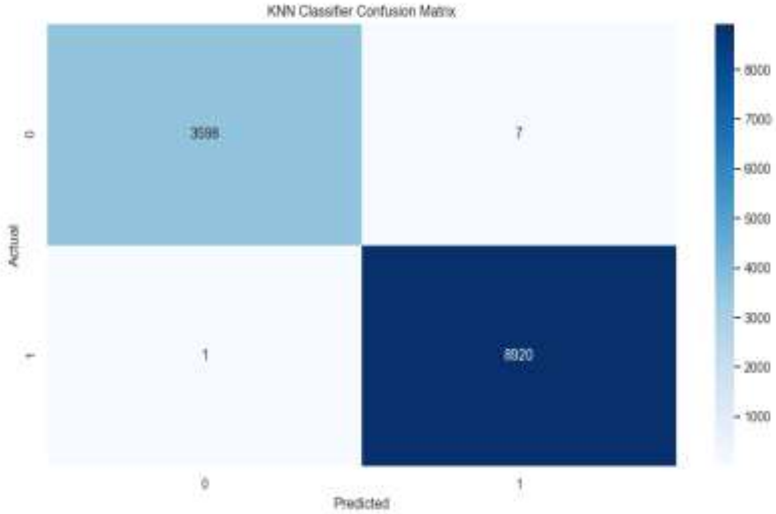

Figure 4.7: confusion matrix for KNN Classifier

The above confusion matrix for Knn classifier shows actual and predicted values. Confusion matrix consists of true positive, false positive, false negative and true negative. False positive and false negative values exceeded values more than one that shows error in predicted values.

Random Forest Classifier is algorithm used to obtain 100 precent predicted value.

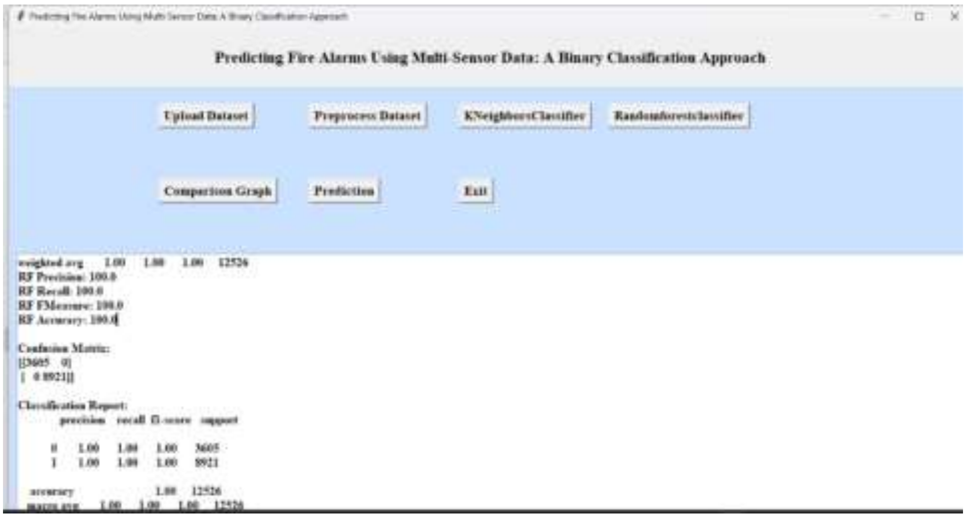

Figure 4.8: Performance evaluation of RF classifier

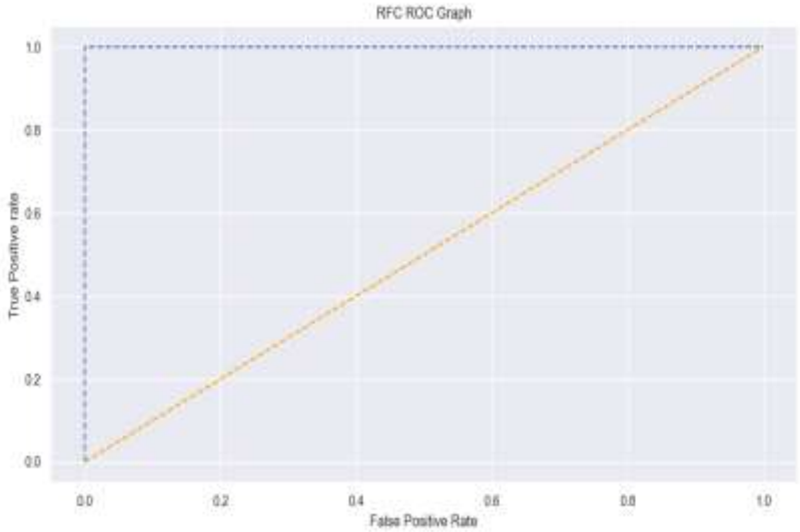

Figure 4.9: ROC graph for Random Forest classifier.

The ROC (Receiver Operating Characteristic) graph for the Random Forest Classifier (RFC) plots the true positive rate and the false positive rate at given threshold settings. With the false positive rate on the x-axis and the true positive rate on the y-axis, where 100% prediction value is achieved. The ROC graph becomes a crucial visualization for evaluating its performance.

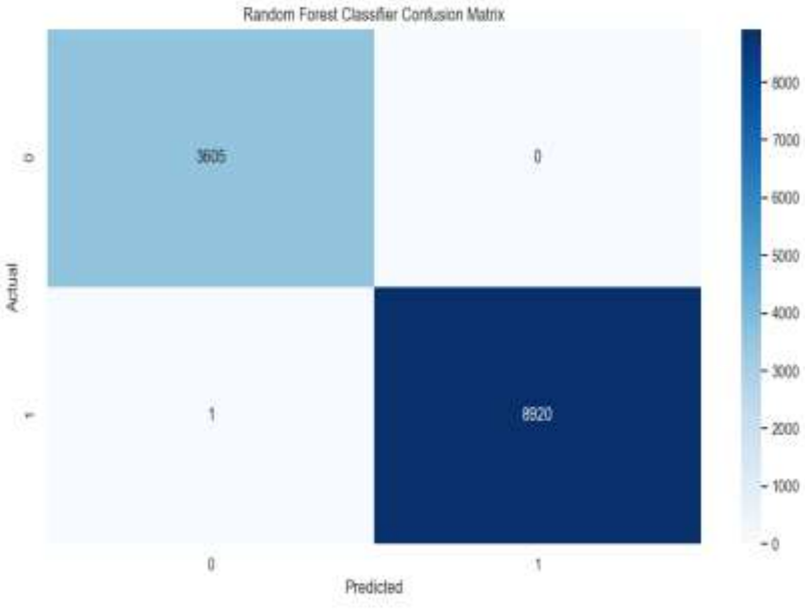

Figure 4.10: confusion matrix for Random Forest Classifier

The above confusion matrix for Random Forest classifier shows actual and predicted values. Confusion matrix consists of true positive, false positive, false negative and true negative. False positive and false negative values did not exceed values more than one which shows no error in predicted values.

Comparing K Neighbour classifier and Random Forest classifier. The comparison graph can be given as

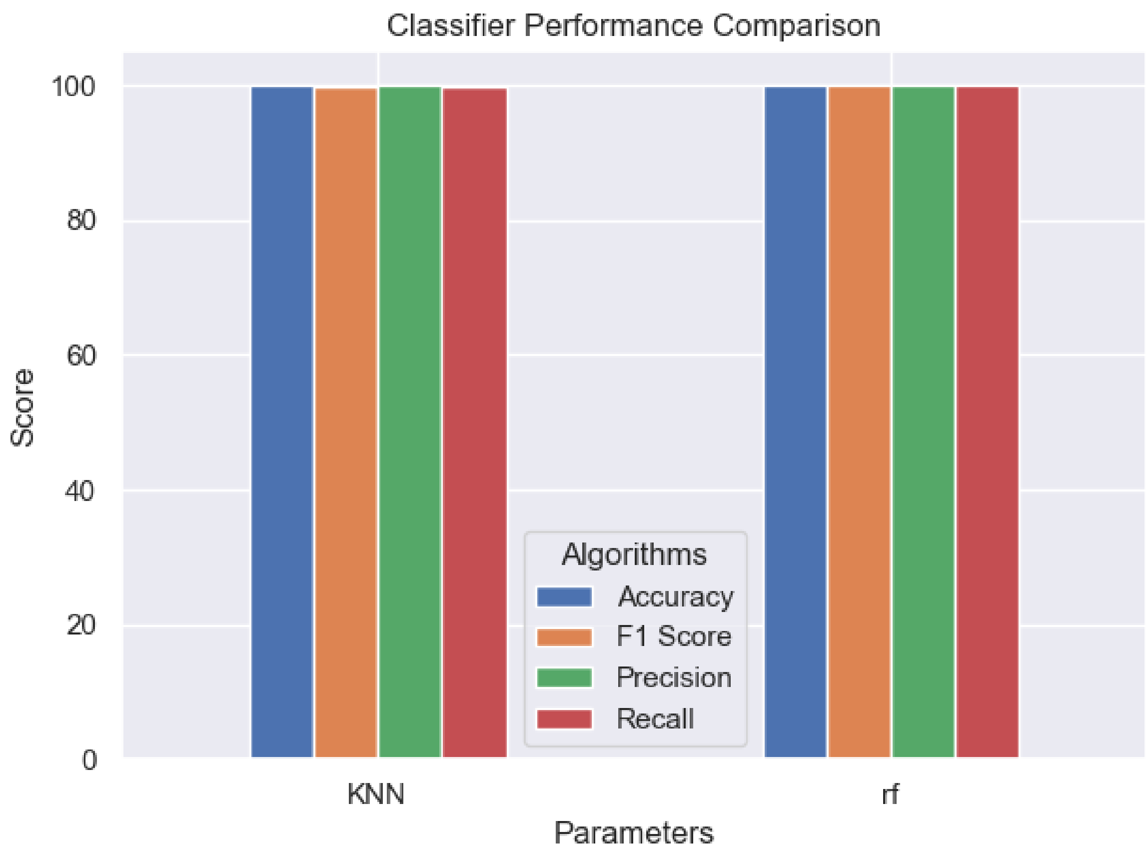

Figure 4.11: Comparison graph for both KNN classifier and RF classifier

The graph above illustrates a comparison between the KNN Classifier and the Random Forest Classifier. The KNN Classifier achieved a predictive accuracy score of 99%, while the Random Forest Classifier achieved a perfect score of 100%, indicating error-free predicted values.

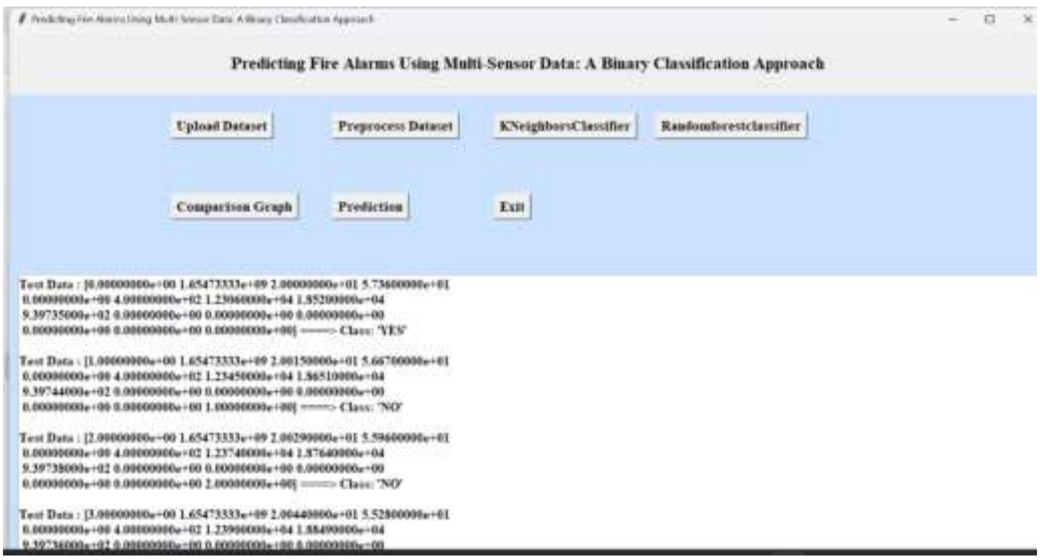

Figure 4.12: Predicted output for proposed method of RF classifier

For testing predicted values, upload test dataset and preprocess the test data then load random forest classifier to check the values. It will give predicted outputs. If the output is '1' then it displays 'YES'. If the output is '0' then it displays 'NO'. If the output is neither '1' nor '0' it displays 'UNKNOWN'.

Table 1 provides a performance comparison of quality metrics for two machine learning models: KNN Classifier and Random Forest Classifier (RFC).

- Accuracy: This metric measures the overall correctness of the model's predictions. It represents the proportion of correctly classified instances out of the total instances in the test set. For both KNN and RF models, the accuracy is exceptionally high, with KNN achieving 98% and RF achieving 100%.
- Precision: Precision is a metric that indicates the accuracy of positive predictions made by the model. It's the proportion of true positive predictions out of all positive predictions made by the model. In this table, both KNN and RF models have a precision of 98% for positive predictions for KNN and 100 % Precision for positive predictions
- Recall: Recall, also known as sensitivity or true positive rate, measures the ability of the model to correctly identify positive instances. It's the proportion of true positive predictions out of all actual positive instances in the dataset. Both KNN and RF models have a recall of 98%. For KNN and 100% for Random forest classifer
- F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall, which is important when dealing with imbalanced datasets or when both false positives and false negatives are costly. In this case, FOR KNN has F1 score of 98%. and RF models have an F1 score of 100%.

In summary, both models (KNN and RF) are performing exceptionally well on the dataset, achieving very high accuracy, precision, recall, and F1 scores. The RF model appears to be performing perfectly (achieving 100% across all metrics), which could potentially indicate a very well-fitted model

Table 1: Performance comparison of quality metrics obtained using logistic regression (KNN) model and random forest classifier (RFC) model.

Model	Accuracy	Precision	Recall	F1 score
KNN model	98	98	98	98
RF model	100	100	100	100

5. CONCLUSION

The integration of multi-sensor data and a binary classification approach has proven to be a pivotal advancement in the realm of fire alarm prediction. By moving beyond the constraints of traditional single-sensor systems, this research has successfully harnessed the power of diverse sensor inputs, including air temperature, humidity, CO2 concentration, molecular hydrogen, ethanol gas, and air pressure. The application of binary classification algorithms has exhibited remarkable efficacy in learning nuanced patterns from the dataset, resulting in a more accurate and reliable prediction of fire-related events. The significance of this work lies not only in its ability to enhance prediction accuracy but also in its capacity to significantly reduce false alarm rates, addressing a longstanding challenge associated with conventional fire alarm systems. The outcomes underscore the potential of leveraging advanced technologies to usher in a new era of fire detection capabilities, thereby mitigating risks, safeguarding lives, and fortifying overall safety measures. The exploration of multi-sensor data and binary classification opens avenues for further innovation in the domain of fire safety. Continued efforts in algorithmic refinement, sensor diversity, and real-time data streaming hold the promise of even greater precision and responsiveness. As technology evolves, the integration of intelligent systems in fire detection not only bolsters our capacity to prevent extensive damage but also underscores the role of cutting-edge approaches in safeguarding human life and property against the persistent threat of fire incidents. By harnessing a diverse array of environmental data, this approach not only enhances the system's ability to distinguish genuine fire events from non-fire disturbances but also marks a departure from the static nature of conventional systems. The adaptability of the system, demonstrated through its improved prediction accuracy and reduced false alarms, highlights the potential for transformative advancements in the field of fire safety.

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