A Novel Hybrid Approach with FireFusionNet for Proactive Fire Accident Prediction in Oil and Gas Refinery Environments

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Abstract: The oil and gas refineries are known for high-risk environments due to their vulnerability towards various calamitous events such as fire accidents, chemical reactions, explosions etc. Since these events are fatal to human lives, it is essential to prevent these accidents by forecasting the threat in the early stages of its occurrences. Accurate prediction of fire accidents can significantly reduce the risk to human safety and improve the operational efficiency. With the emergence of advanced techniques such as Machine Learning (ML), it is practically feasible to forecast the threats in real-time and help the risk operators to take preventive measures. This research focuses on developing a hybrid approach that integrates three different ML models such as Random Forest, XGboost and Neural network for dynamic risk analysis by estimating the probability of accidents and their severity with respect to the historical data available. The hybrid model known as FireFusionNet is a prediction approach which can sense and forecast the risk based on the trained data with respect to various oil and gas refineries. The potential risks are assessed for each cause-consequence pair using the HAZOP technique and the risks are prioritized based on their levels. Experimental results show that the proposed FireFusionNet approach ensures the resiliency of the refinery by accurately predicting the fire accidents with an accuracy of 100%.

Keywords: Fire Accident Prediction, Oil and Gas Refinery, Machine Learning, Random Forest, XGBoost, Prediction Accuracy

1. Introduction

Oil and gas refineries are majorly used in the extraction of oil from the petroleum products. These refineries operate under catastrophic environments and are always under risk due to highly inflammable and explosive materials (Fazli et al., 2020) (Dugué, 2017). This increases the potential risk for human lives and to the operational environment. Several threats pose a significant risk to the oil refineries which directly or indirectly affect the resiliency and integrity of the environment. Besides, the waste generated by the refinery can be lethal due to the inclusion of various hazardous substances in it (Moreno-Sader et al., 2020). A major portion of the wastage is released into the rivers and other water bodies, which pollutes the river habitat and makes it hazardous for the animals living there. In addition, the wastage also pose indirect risk in terms of releasing harmful chemicals and electronic toxic materials into the outside environment (Saloua et al., 2019) (Bouafia et al., 2020) . If not assessed properly, the threats posed by the refinery plants can endanger human lives and destroy the entire plant. In this context, a lot of safety and precaution measures are taken to ensure the safety of workers and plants. These measures help in handling the uncertainties and common risks associated with oil refineries such as explosion, fire accidents etc (Samia et al., 2018) (Yang et al., 2020). With the passing years, the chances of accidents also increases. Hence, industries and oil refineries perform risk analysis to investigate the impact of accidents, frequency of occurrences, and reason for occurrence based on the previous and present scenarios. In general, the process of risk analysis involves three prominent stages namely risk identification, risk estimation, and risk assessment (Gauthier et al., 2018) (Sun et al., 2018). By estimating the risk, necessary measures can be taken to mitigate the effect and reduce the possibility of occurrence. Usually, safety measures are applied in the initial stages of operational process i.e., during the design stage. Risk analysis is profoundly performed in oil and gas refineries to identify the risk using different assessment techniques such as quantitative risk assessment (QRA), probabilistic safety analysis (PSA) (Mohammadfam & Zarei, 2015) (Ade & Peres, 2022), and maximum reliable accident analysis (Ramos et al., 2021). However, the static nature of these techniques does not allow them to consider the dynamic changes that occur during the process. As a result, these techniques generate results with uncertainties. There is a need for dynamic risk assessment techniques which incorporate the rapid changes that occur during the process and help to understand the consequence of the accidents and make timely decisions to prevent them. In this context, this research intends to employ Machine Learning (ML) based prediction framework for forecasting fire accidents.

The main contributions of this study are as follows:

- This paper designs a hybrid framework that combines Random Forest (RF), XGboost, and Neural Network for predicting the possibility of fire occurring in oil and gas refineries.
- A diverse dataset is considered for training the hybrid model known as FireFusionNet for fire accident prediction. Different parameters related to humidity, temperate, CO_2 (Carbon dioxide) concentration are considered to increase the diversity of the dataset.
- The hybrid approach leverages the strengths of three ML algorithms and forms a synergistic framework to enhance prediction accuracy and robustness. The hybrid model captures intricate patterns of the data for accurate forecasting in a complex refinery environment.
- A Gradio interface is created for user interaction to carry out real-time data monitoring and fire prediction. This system takes input values for various environmental features and predicts the likelihood of a fire using a hybrid model.
- The performance of the hybrid model is compared with various existing models such as Logistic Regression, Decision Tree, KNN classifier, Support Vector Machine (SVM) classifier, and Multilayer Perceptron (MLP) for validating the efficacy of the FireFusionNet model.

The rest of the paper is structured as follows: Section II discusses the review of existing literary works related to safety of different oil and gas refineries. Section III provides a brief description of the proposed methodology including the implementation of the FireFusionNet approach. Section IV discusses the simulation results and Section V concludes the paper with prominent research observations.

2. Related Works

Various research works have focused on developing forecasting fire accident, risk identification and assessment techniques (Petrovskiy et al., 2015) (Badida et al., 2019) (Ishola et al., 2020). Techniques such as traditional risk analysis processes, dynamic risk assessment techniques, failure analysis and estimation methods based on ML and neural network architectures. In most of the cases, techniques based on fuzzy logic, signal processing are employed for determining and predicting the failures of sensors and devices responsible for predicting the accidents in oil refineries. However, these techniques are not effective in yielding better performance in real-time scenarios due to their inability to cope with the complex environment. It is challenging to modify the algorithm based on the real-time changes and due to this the algorithm fails to identify new types of accidents or incidents. The work presented in (Yang et al., 2017) aimed to overcome this issue and developed an optimized model based on the convolutional neural network (CNN) for determining different types of failures. The model learns from previous failure information without depending on the sensor data. The CNN model is designed to classify the sensor failures into different categories in order to improve the accuracy of the model. An ensemble of techniques is deployed to enhance the classification ability of the CNN model. Research works based on DL have gained huge prominence since they can handle complex data effectively and its ability to learn from previous instances. A prediction model is designed in (Kim, 2021) for minimizing the damages caused by fire accidents. The model intends to assist the fire fighters by providing swift response and thereby significantly reducing the impact of the fire accident. Since the model is trained to predict the possible threats in the early stages, the risk can be mitigated. In addition, the model also provides details about the location of a fire accident, which helps in making timely decisions. The parameters related to the accident are analyzed in a comprehensive manner and are used to train the ML model. Results show that the proposed approach is highly effective in predicting fire accidents. The authors in (Arabahmadi et al., 2023) employed an Artificial Neural Network (ANN) for predicting accidents in oil industries. The study states that there is a great scope of integrating AI models for achieving better prediction accuracy and thereby ensuring the safety of the critical oil and refinery industry.

3. Proposed Research Methodology

A hybrid ML model combining Random Forest, XGBoost and Neural Network is designed in this research for predicting the fire accidents in oil and gas refineries. The proposed approach intends to perform risk analysis for analyzing the impact of fire accidents and thereby mitigate the effect. The stages involved in the implementation of the proposed approach are discussed in the below sub sections.

3.1 Dataset Details

The data for the experimental analysis is collected from the Kaggle dataset and the link for accessing the data is given below:

https://www.kaggle.com/datasets/deepcontractor/smoke-detection-dataset

The data is saved in the .CSV format. The features are related to air quality, temperature, humidity, and particulate matter which are essential to understanding the conditions that may indicate the presence of a fire. Overall, the dataset contains 62,630 total records for predicting the fire. Fire requires a certain temperature to initiate and sustain and it is essential to monitor air temperature to identify the conditions that are responsible for ignition and spread of fires. Another important factor is the humidity of the air inside the oil refinery. Humidity defines the amount of moisture or water vapor present in the air. Lower humidity levels can contribute to dry conditions, making it easier for fires to ignite and spread. Monitoring humidity helps assess the moisture content in the air, influencing the combustibility of materials. Total Volatile Organic Compounds (TVOC) is measured in terms of parts per billion. The TVOC is measured in terms of concentration of various organic compounds that are present in the air. Different organic compounds that are released during the fire accidents indicate the level of fire and increased TVOC levels indicate the presence of flammable materials or ongoing combustion processes. The equivalent concentration of CO_2 (eCO_2) is used for calculating the TVCO values. Since the level of CO_2 plays a crucial role in indicating the combustion process, it is essential to determine the concentration level and thereby gain information about potential fire incidents. The dataset also contains the details about Raw Molecular Hydrogen (Raw H2) which designs the concentration of raw molecular hydrogen in the air. A higher level of H2 defines the presence of highly inflammable gas and thereby helps in identifying potential fire hazards. The measurement of Raw Ethanol indicates the concentration of raw ethanol gas in the air. The presence of raw ethanol indicates the presence of flammable liquids. Ethanol is highly combustible, and its detection can be relevant for fire prevention. In addition to these chemical compounds, another important factor that has to be monitored is the pressure of the air inside the refinery environment. The variations in the atmospheric pressure has a greater impact on the fire spread. Monitoring air pressure can help in understanding atmospheric conditions that may impact the initiation and progression of fires.

3.2 Data Preprocessing

The data is preprocessed in order to make it suitable for the classification and prediction tasks. In this stage, the data collected from the dataset is filtered to remove the redundant data and uncertainties. This research employs an Exploratory Data Analysis (EDA) technique for removing unnecessary columns from the data and thereby describes the statistical data of each feature. In addition, the presence of null values in the dataset is checked and removed to improve the performance of the hybrid ML model. The EDA is a method used for analyzing the data with the help of visual techniques. In this work, the EDA was used to explore and understand the behavior of the parameters in the oil and gas refinery, to identify the fire accident patterns, and possibilities of accidents. The patterns are then used to validate the assumptions made with the help of statistical tools and graphical representations. In general, the data is represented in terms of rows and columns. A describe() function is used for finding out different aspects of data such as count of data points, extreme values, standard deviation, null values, and missing values by performing fundamental statistical analysis. While performing EDA, the missing values or the null values are skipped automatically and the distribution of data across the rows and columns are obtained using the describe () function. The missing values in the dataset can occur when no data is provided for one or more elements in a row or column. If the information is not available for each element then that particular block in a row or column shows null value. This issue can be more complicated and can cause more arduous problems in practical or real-time applications. A pie chart is plotted to visualize the distribution of the "Fire Alarm" classes as shown in figure 1. In addition, a bar graph is plotted to determine the cases of fire alarm as shown in figure 2.

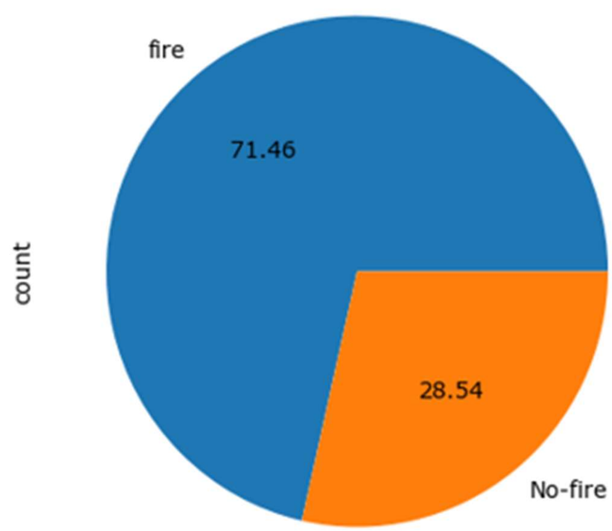

Figure 1 : Visualization of Fire alarm possibilities

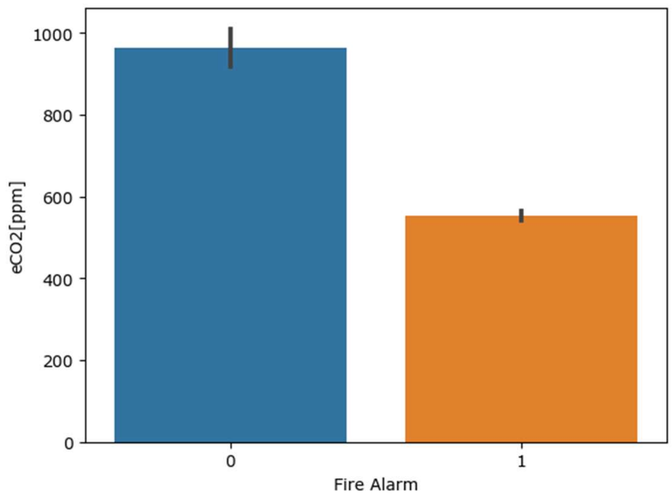

Figure 2 : Distribution of Fire alarm classes

As observed from figure 1, 71.46 % of the instances indicated the presence of fire alarm, and 28.54 % of the instances indicated no-fire. After preprocessing the data, the data is split into training and testing data.

3.4 Feature Selection

In this stage, the essential features are selected for finding specific and important features and selects only a subset of the relevant features. A Chi-Square Method is used for selecting the features and the same is evaluated using a Chi square test. The dataset is filtered using a correlation matrix and in most of the cases, the filtering is done using the chi square test. Correlation here refers to the process of defining the state of variables and the dependency between them. In other words, correlation is a statistical term which describes the extent to which the two variables vary with respect to the changes in them. In the supervised feature selection process, the correlation is calculated between the features and the class label. In this research, the features are selected by evaluating the correlation between two features. In general, a feature is considered as good if it is relevant to the class and is not redundant to any other features. Implementation of correlation as a measure to identify relevant features will help to select appropriate features from the feature set i.e., the feature will be considered as good if it is correlated only to the feature subsets and not to any other features. Further, the correlated features are used for further process.

In this process, the dataset is split into features (X) and the target variable (y). The chi-square test is then applied to assess the relationship between each feature and the target variable. The p-values from the chi-square test are extracted, and the features are sorted based on these p-values in descending order as shown in figure 3.

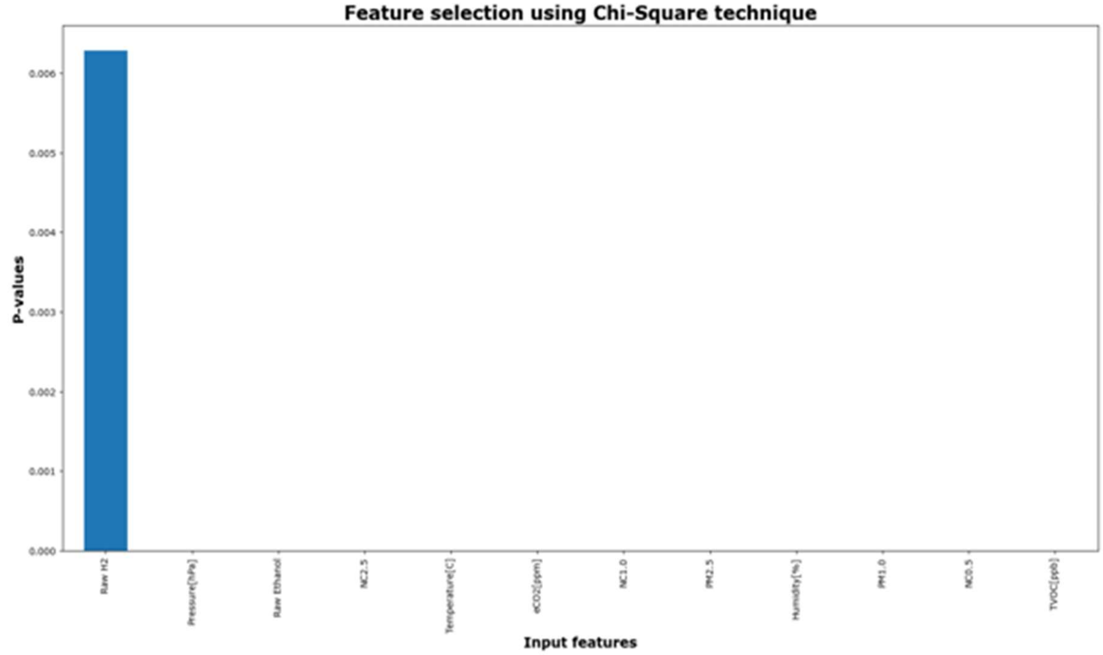

Figure 3 : Feature selection using the chi square test

Using the chi squared test it can be identified whether a feature is correlated with target variable or not using p-value with certain assumptions and hypothesis:

H0 (null hypothesis):- There is no relationship between categorical feature and target variable

H1 (alternative hypothesis):- There is some relationship between categorical feature and target variable

If p-value ≥ 0.05; then the null hypothesis is rejected and this states that there is no relationship between target variable and categorical features. If p_value < 0.05, then the alternative hypothesis is rejected and it is considered that there is some relationship between target variable and categorical features and all those features are selected for further processing using the hybrid model. In this research, all values were found to be less than 0.05 hence none of the features were removed.

After selecting the features, they are standardized using a StandardScaler function. After scaling, the data is split into training and testing sets using train_test_split, with 70% of the data used for training (X_train, y_train) and 30% for testing (X_test, y_test). Here, the RF classifier is trained using the dataset and its performance is evaluated in the context of Fire Hazard Analysis (FHA).

3.5 Risk score assignment and risk assessment using HAZOP

A predict_proba method is used to obtain the predicted probabilities for the positive class (class 1, in this case, the 'Fire Alarm' being True) from the trained model. The predicted risk scores along with the actual 'Fire Alarm' values from the test set are combined into a DataFrame and sorted based on the predicted risk scores in descending order. Based on this, the risk score is computed and is compared with the target feature. For each feature in the dataset, new columns are created for each guide word and the columns represent deviations from the original values based on the specified guide words. The risk is assessed using a Hazard and Operability Study (HAZOP) technique which is commonly used in various industries, to identify and assess potential hazards associated with the design, operation, and maintenance of processes. In this research, HAZOP is used for assessing the fire hazards and assessing the risk associated with it.

A correlation matrix is calculated, and potential causes and consequences are identified based on positive and negative correlations with the 'Fire Alarm' feature. Further based on the correlation, the severity, likelihood, and detectability are calculated for each potential cause-consequence pair. These metrics are then used to assess the risk level. Risk assessments are calculated for each cause-consequence pair, and the risks are prioritized based on their levels. In this research, the causes and consequences are prioritized based on the level of risk. A risk score is calculated for each row in the dataset as a weighted sum of features and the risk scores are normalized between 0 and 1 using min-max scaling, and a threshold is used to classify the risk into high or low risk.

3.6 Prediction of Fire accidents using the FireFusionNet model

The hybrid model is designed for fire prediction by combining predictions from individual machine learning models. In the FireFusionNet model, fire represents the domain of prediction, fusion implies the merging or blending of different elements. In this context, it indicates the combination of various machine learning models, specifically Random Forest (RF), Neural Network, and XGBoost. Net refers to the neural network component of the model.

The RF algorithm is a supervised classification algorithm which creates a forest with multiple trees. Higher the number of trees in the forest, higher is the accuracy results. The RF model is selected mainly because of its ability to handle the missing values. In case, if the number of trees are more, the RF classifier will not overfit the model and can effectively process the categorical values. For prediction, the test features are selected and the rules are set for each randomly created decision tree to predict the outcome and stores the predicted outcome (target). Further, the votes for each predicted target are calculated and the highest voted predicted target is considered as the final prediction outcome. The XGBoost algorithm is an ensemble learning model which is known for its excellent prediction performance. XGBoost is based on the concept of gradient boosting, a ML-based framework where weak learners (typically decision trees) are trained sequentially to correct the errors made by the preceding models. It builds a strong predictive model by combining the predictions of multiple weak models, each focusing on the residual errors of the ensemble. The RF and XGBoost algorithms are enabled with the neural network model in order to effectively process large scale data and improve the performance in terms of predictions. In this research, predictions are made using each individual model on the test data (X_test). The predictions from individual models are combined using a FireFusionNet approach, specifically by taking the average of the predicted probabilities and rounding to obtain a binary prediction. The performance of the FireFusionNet model is evaluated and the results are discussed in the next section.

4. Results and Discussion

The FireFusionNet model is tested and evaluated in terms of predicting the fire accidents and the risk analysis is performed to validate the accuracy.

4.1 Experimental Details

From the data collected, the concentration of particulate matter in the air with sizes less than 1.0 µm (PM1.0) and 2.5 µm (PM2.5) is measured and the measured values are included in the dataset. Particulate matter in the air can be generated by combustion processes. Elevated levels of PM may indicate the presence of smoke, which is a byproduct of fires. Monitoring particle concentration can help detect and assess fire-related pollutants in the air. Based on these factors, the model is trained to generate the fire alarm wherein the model flags the value as "1" if a fire is detected and is detected as "0" under no fire existence. This is the ground truth label indicating whether a fire is detected. It is a crucial feature for training a supervised machine learning model to predict fire incidents based on the other environmental variables. A CNT (Sample Counter) parameter is used for defining the number of samples. The CNT variable helps in tracking the number of data points collected, ensuring a systematic approach to data analysis. While the timestamp in Coordinated Universal Time (UTC) in seconds. The timestamp provides temporal information, allowing for the analysis of fire incidents over time and the correlation with specific environmental conditions. On the other hand, the number concentration of particulate matter is also determined. This differs from PM because NC gives the actual number of particles in the air. The raw NC is also classified by the particle size: < 0.5 µm (NC0.5); 0.5 µm < 1.0 µm (NC1.0); 1.0 µm < 2.5 µm (NC2.5). Similar to PM, monitoring the number concentration of particles with different size classifications provide insights into the presence of combustion-related pollutants in the air. In summary, each feature contributes valuable information to the overall context of fire prediction by capturing different aspects of the environment, combustion processes, and potential fire hazards. Integrating these features in a machine learning model allows for a holistic approach to predicting and preventing fire accidents.

4.2 Performance Evaluation

The performance of the FireFusionNet model is determined using various different evaluations which are expressed using the below equations. These metrics are the elements of the confusion matrix which provides a clear output for multiple classes.

$$\boldsymbol{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \dots (1)$$

$$\boldsymbol{Recall} = \frac{TP}{TP+FN} \dots. (2)$$

$$\boldsymbol{F1\ score} = \frac{2 * Precision * Recall}{Precision + Recall} \dots. (3)$$

$$\boldsymbol{Precision} = \frac{TP}{TP+FP} \dots (4)$$

Where TP, TN, FP, and FN represent True positives, True negatives, False positives, and False negatives respectively. The performance is evaluated with respect to classification accuracy, and the results of the simulation analysis are discussed as follows:

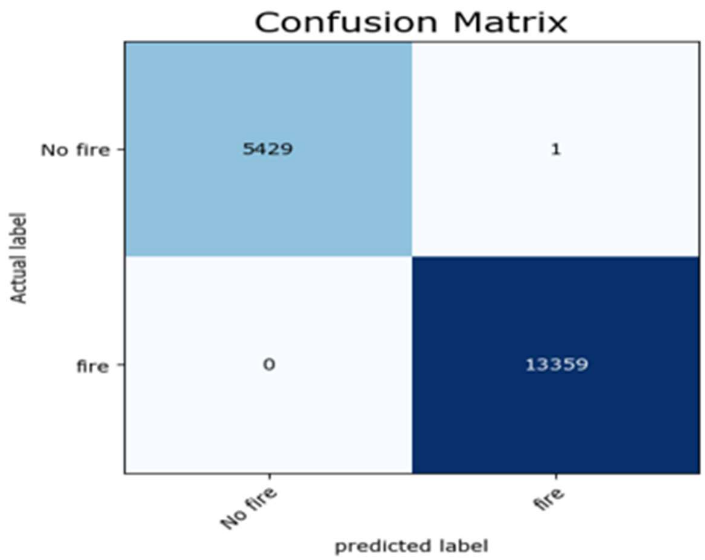

Figure 4 : Confusion matrix of the FireFusionNet model

As observed from the confusion matrix, the FireFusionNet model achieves an accuracy of 100 %. The classification performance of the classifier is tabulated in table 1.

Table 1 : Classification results

	Precision	Recall	F1-Score	Support
0	100 %	100 %	100 %	5430
1	100 %	100 %	100 %	13359
Accuracy	-	-	100 %	18789
Macro Avg	100 %	100 %	100 %	18789
Weighted Avg	100 %	100 %	100 %	18789

In addition, the performance of the FireFusionNet model is compared with other ML models and the results are tabulated in table 2.

Table 2 : Results of the comparative analysis

Metrics	KNN	Logistic Regression	Decision Tree	SVM	Multilayer Perceptron	FireFusionNet
Accuracy	99.85 %	89.82 %	99.99 %	97.16 %	99.89 %	100 %
Precision	99.88 %	91.05 %	100 %	97.18 %	99.85 %	100 %
Recall	99.91 %	95.16 %	99.99 %	98.90 %	99.99 %	100 %
F1 score	99.90 %	93.06 %	99.99 %	98.03 %	99.92 %	100 %

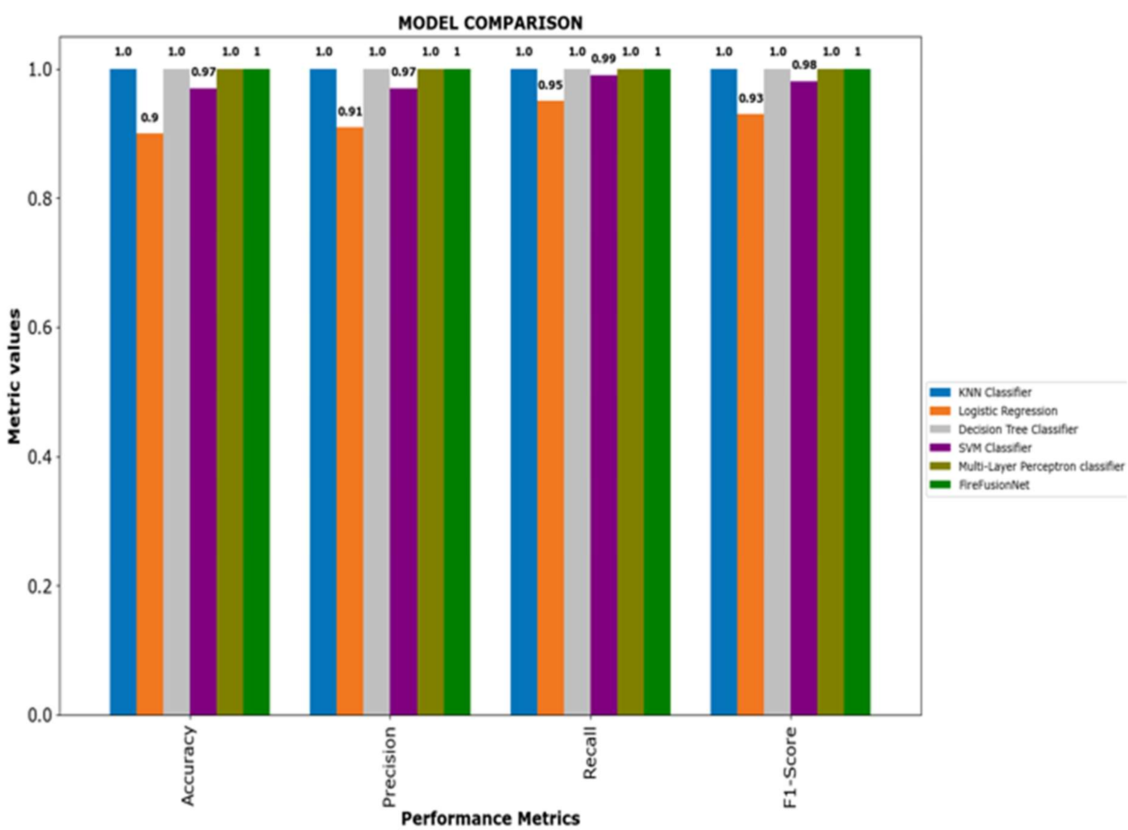

Figure 5 : Results of the comparative analysis

As observed from the results, the proposed research achieves an excellent accuracy of 100 % compared with other ML classifiers.

This research implements a real-time data monitoring and fire prediction system using Radio for user interaction. This system takes input values for various environmental features and predicts the likelihood of a fire using a hybrid model. The script prompts the user to input values for various environmental features, such as temperature, humidity, TVOC, eCO2, raw H2, raw ethanol, pressure, PM1.0, and NC0.5. The script then uses the trained individual models to make predictions on the input data. The predictions from these models are combined using a hybrid approach, such as averaging. Further, a Gradio interface is designed for real time prediction from user input. The Gradio interface allows the users to interact with the system using a graphical user interface (GUI). Users can input values through the GUI, and the system will provide predictions in real-time.

5. Conclusion

This research presents a novel hybrid approach that combines three ML models namely Random forest, XGboost classifier, and neural network for predicting the fire accidents in the oil and gas refinery. The proposed hybrid approach is trained using a diverse dataset which includes various parameters such as air temperature, pressure, humidity, CO_2 concentration etc for achieving an accurate prediction. The data is visualized using the EDS technique which removes the null values and missing values for improving the performance of the hybrid model. The essential features are selected using the Chi square test and the features were used for performing risk analysis. The performance of the FireFusionNEt model is tested and evaluated using various evaluation metrics and results show that the proposed model achieves a phenomenal accuracy of 100% in comparison to other ML models. For future research, this work can be extended to implement a deep reinforcement learning (DRL) model for adapting to the dynamic condition of the refinery environment. The model can also be extended to handle large-scale datasets efficiently in real-time environments.

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