International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

PREDICTING CAR FIRE ACCIDENTS USING MACHINE LEARNING MODELS

Keerthana U[1], Dr.Glory Vijayaselvi K[2]

Student, PG Department of Computer Science and Technology, Women's Christian College, Chennai, 20pct27@wcc.edu.in
Associate Professor, Department of Computer Science (Shift II), Women's Christian College, Chennai, gloryvijayaselvi@wcc.edu.in

ABSTRACT :

This research addresses the growing concern of unexplained car fires, by employing machine learning techniques to predict fire occurrences. By analyzing comprehensive vehicle characteristics, including fuel type, engine specifications, age, safety ratings, and environmental factors like population density, the study aims to identify key predictors of fire incidents. Using real-world data from sources like Kaggle and the National Fire Incident Reporting System (NFIRS), machine learning models such as Random Forest, Support Vector Machine (SVM), and Logistic Regression were applied. Techniques like hyperparameter tuning and ensemble methods were used to enhance model accuracy. The results indicate that older vehicles, higher horsepower, certain fuel types, and lower safety ratings are significant contributors to increased fire risk. This predictive approach can aid vehicle manufacturers, regulatory bodies, and car owners in identifying high-risk vehicles and implementing preventive measures, ultimately contributing to improved vehicle safety and reduced fire hazards.

Keywords: Car Fire Prediction, Machine Learning, Random Forest, Support Vector Machine (SVM), Logistic Regression, Ensemble Learning, Vehicle Safety, Environmental Factors, Fire Risk Prediction.

1.) INTRODUCTION

Unexplained vehicle fires, particularly those caused by leaky fuel systems, present a serious threat to public safety, often leading to property damage, injuries, or fatalities. Despite advances in automotive technology and safety standards, these incidents continue to occur, with root causes frequently remaining unidentified. This poses challenges for both manufacturers and regulators in preventing and mitigating such risks. The ability to predict potential fire hazards before they occur is critical in enhancing vehicle safety, protecting consumers, and minimizing economic losses.

This research focuses on developing a predictive framework that analyzes vehicle characteristics and environmental factors to assess the likelihood of car fires caused by fuel system leaks. By utilizing large-scale datasets that capture vehicle specifications and real-world fire incidents, this study aims to uncover key factors contributing to fire risks and offer early warning mechanisms. Such predictive capabilities could empower manufacturers to design safer vehicles, help regulatory agencies establish more stringent safety guidelines, and provide vehicle owners with critical information to make informed maintenance and usage decisions.

The broader impact of this research lies in its potential to transform how fire risks are managed in the automotive industry. By shifting from reactive measures to predictive, data-driven approaches, this study contributes to creating safer transportation systems and preventing life-threatening incidents.

2.) LITERATURE REVIEW

[1] *India Today*, May 19, 2024, "Moving car catches fire at Delhi-Meerut Expressway, driver escapes unhurt" A moving car on the Delhi-Meerut Expressway caught fire, resulting in the vehicle being completely burned down. The fire spread rapidly after the driver managed to escape. The cause of the fire has not been explicitly stated.

[2] *The New Indian Express*, June 08, 2024, "65-year-old dies after moving car catches fire in Kozhikode" A car caught fire near Konnad Beach in Kozhikode, leading to the death of the 65-year-old driver. The probable cause of the fire was an electrical short circuit, and the fire quickly engulfed the car before any rescue could be made.

[3] *The Hindu*, August 22, 2024, "Car catches fire near Ambur town on Chennai-Bengaluru Highway" A car on the Chennai-Bengaluru Highway caught fire due to a suspected electrical short circuit. The three passengers escaped unhurt, but the vehicle was completely destroyed.

[4] *The Hindu*, September 03, 2024, "Car catches fire near Katpadi in Vellore" A mini-van in Vellore caught fire due to a suspected electrical short circuit. The driver escaped unhurt, but the vehicle was completely gutted before the fire was controlled.

[5] Li, Qin, Luo, Ling, "Diagnosis of Gasoline Engine Misfire Faults Using an Improved YOLOv8 Model, 2024" The study diagnoses gasoline engine misfires using sound signals and an improved YOLOv8 model. Sound signals are transformed into time-frequency images, enabling accurate misfire detection. Future research will explore data augmentation and unsupervised learning.

[6] Md Kamrul Hassan, "Fire Incidents, Trends, and Risk Mitigation Framework of Electrical Vehicle Cars in Australia, 2023" The study identifies key EV fire risks (batteries, charging systems) and proposes a safety framework with recommendations for battery management and safe charging. Future work will improve battery tech, charging infrastructure, and fire detection systems.

[7] Mohd Zahirasri Mohd Tohir, "Probabilistic Design Fires for Passenger Vehicle Scenarios, 2021" The study develops heat release rate curves for passenger vehicle fires and applies a probabilistic calculation for parking structures. Future research will enhance models to predict fire severity based on vehicle types and parking configurations.

[8] Haavard Boehmer, "Modern Vehicle Hazards in Parking Structures and Vehicle Carriers, 2020" The study explores fire risks posed by modern vehicles, especially EVs, in parking structures and vehicle carriers. Future research will focus on advanced fire suppression systems and updated safety standards.

[9] Myoung-Young Choi, "Fire Risk Assessment Using Statistical Machine Learning and Risk Indexing, 2020" The study introduces a fire risk index (NKFRI) using machine learning to predict fire occurrences. Future research will refine predictive models, expand variables, and apply the method to various facilities.

[10] Mohd Zahirasri Mohd Tohir, Michael Spearpoint, "Probability of Fire Spread Between Vehicles in Car Parking Buildings, 2017" The study investigates fire spread between vehicles in parking structures, revealing higher risks in close proximity. Future work will explore fire suppression and sprinkler systems to reduce spread probability.

[11] Lakshmisri Surya, "Risk Analysis Model That Uses Machine Learning to Predict the Likelihood of a Fire Occurring at a Given Property, 2017" The study develops a machine learning model for fire risk prediction, improving resource allocation for fire prevention. Future work will enhance algorithms and integrate real-time data for better fire management.

[12] Xiao-hui Jiang, "Full-scale Experimental Study of Fire Spread Behaviour of Cars, 2017" The study conducts full-scale experiments to analyse fire spread in cars, highlighting the impact of interior materials and ventilation. Future research will focus on fire retardant materials and ventilation management for improved fire safety.

Img. Source : The Hindu

Img. Source : The New Indian Express

3.) DATA COLLECTION

The data for this research was sourced from Kaggle, a platform that offers a wide array of datasets for machine learning projects. Two CSV files were provided: one for the training data (***train.csv***), which initially consisted of 58,592 rows and 44 columns, and another for the test data (***test.csv***), comprising 39,063 rows and 43 columns. These datasets contained critical vehicle-specific features such as fuel type, car age, max torque, max power, and NCAP safety ratings, alongside environmental factors like population density. The final cleaned datasets, after adding the target variable (fire occurrence), were reduced to 19 features for both training and test datasets.

The figure below illustrates the subset of the cleaned training data.

fuel_type	age_of_car	population	max_torqu	max_powe	engine_typ	displacem	cylinder	transmissi	gear_box	gross_weig	turning_rac	ncap_ratin	make	model	segment	is_esc	is_tpms	fire_occurrence
CNG	0.05	4990	60	40.36	F8D Petrol	796	3	Manual	5	1185	4.6	0	1	M1	A	FALSE	FALSE	FALSE
CNG	0.02	27003	60	40.36	F8D Petrol	796	3	Manual	5	1185	4.6	0	1	M1	A	FALSE	FALSE	FALSE
CNG	0.02	4076	60	40.36	F8D Petrol	796	3	Manual	5	1185	4.6	0	1	M1	A	FALSE	FALSE	FALSE
Petrol	0.11	21622	113	88.5	1.2 L K12N	1197	4	Automatic	5	1335	4.8	2	1	M2	C1	TRUE	FALSE	TRUE
Petrol	0.11	34738	91	67.06	1.0 SCe	999	3	Automatic	5	1155	5	2	2	M3	A	FALSE	FALSE	TRUE
Diesel	0.07	13051	250	113.45	1.5 L U2 CR	1493	4	Automatic	6	1720	5.2	3	3	M4	C2	TRUE	TRUE	FALSE
Diesel	0.16	6112	200	88.77	1.5 Turboc	1497	4	Manual	5	1490	5	5	4	M5	B2	FALSE	FALSE	FALSE
Petrol	0.14	8794	113	88.5	K Series Du	1197	4	Manual	5	1335	4.8	2	1	M6	B2	FALSE	FALSE	TRUE
Diesel	0.07	6112	250	113.45	1.5 L U2 CR	1493	4	Automatic	6	1720	5.2	3	3	M4	C2	TRUE	TRUE	FALSE

Fig. 1 – Subset of the cleaned data

4.) NORMALIZATION TECHNIQUES

A. Standard Scaling

Standard scaling transforms features by removing the mean and scaling to unit variance. This technique ensures that the features are centered around zero with a standard deviation of one, which is particularly useful for algorithms that rely on the distance between data points, such as Support Vector Machines and Logistic Regression.

StandardScaler

The StandardScaler from sklearn.preprocessing is utilized to standardize the numeric features, ensuring that they contribute equally to the distance computations in the model training process. The formula used for standard scaling is:

$$X' = (X - \mu)/\sigma$$

where:

- **X' is the standardized value,**
- **X is the original value,**
- **μ is the mean of the feature,**
- **σ is the standard deviation of the feature.**

B. One-Hot Encoding

One-hot encoding is employed to convert categorical variables into a format that can be provided to machine learning algorithms to improve predictions. Each category level is transformed into a binary column, allowing the model to learn from categorical data effectively.

C. Handling Missing Values

The preprocessing pipeline includes handling missing values for both numeric and categorical features. For numeric features, the median value is used to fill in missing data, while categorical features are filled with the most frequent value (mode).

D. Extracting Numeric Values

Numeric values from text-based features, such as max_torque and max_power, are extracted using regex patterns. This process ensures that consistent numeric values are utilized, preventing errors that could arise from processing raw text data. By applying regex, you can efficiently isolate and clean numerical data, facilitating more accurate modelling. For instance, a string like "Max Torque: 250Nm@2750rpm ", a regex pattern like \d+ can extract the number 250 by identifying patterns like "Nm" and "bhp", ensuring that the numeric portion is retained for further calculations. The function uses the pattern matching expression:

```
pattern = '(\d+.?\d*)Nm'
```

E. Converting Data Types

Columns are converted to appropriate numeric types to ensure that all features are in a format suitable for model training. This conversion is crucial for maintaining data integrity and consistency.

F. Creating Target Variable

The synthetic target variable, fire_occurrence, is established based on specific thresholds derived from both industry research and safety standards. This variable is crucial for the predictive modelling process and encompasses several key features. For instance, the age of the car is set at over 0.07 years to account for newer vehicles, which tend to have improved safety features. The fuel types considered—petrol, diesel, CNG, and hybrid—are selected based on findings that demonstrate how different combustion properties can influence fire risks. Additionally, numeric thresholds for maximum power (greater than 60) and maximum torque (greater than 90) reflect research indicating that higher performance vehicles may be associated with overheating and fuel system integrity issues. A population density exceeding 300 is employed, as studies have shown a correlation between urban density and vehicle incident rates. Finally, an NCAP rating of 3 or lower signifies vehicles with less robust safety features, which may contribute to an increased risk of fire. These thresholds are informed by literature on vehicle safety and fire risks, drawing insights from journals such as the Fire Safety Journal and reports from the National Highway Traffic Safety Administration (NHTSA) on vehicle safety.

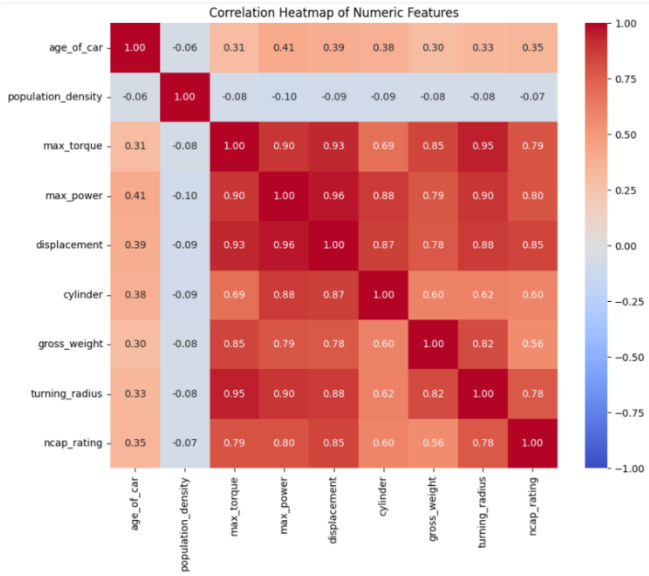

Fig. 2 - Correlation Heatmap of Numeric Features

5.) MACHINE LEARNING TECHNIQUES

In this research, we employed a diverse set of machine learning techniques to predict vehicle fire occurrences, focusing primarily on Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and an ensemble model. While methods like Naive Bayes and Neural Networks are also available, we chose LR for its simplicity and interpretability, SVM for its robustness in high-dimensional data, and RF for its ability to capture complex feature interactions and high accuracy in predictive tasks. Previous studies, such as those by Hassan et al. (2023)**[6]** and Choi & Jun (2020)**[9]**, highlighted the effectiveness of RF in fire risk modeling, which informed our selection. The ensemble model further enhanced predictive performance by integrating multiple classifiers, improving overall robustness and accuracy.

A. Logistic Regression:

Logistic Regression was utilized as a baseline classifier due to its simplicity and interpretability in binary classification tasks. It provided insight into the linear relationships between the features and vehicle fire risk. Cross-validation results indicated a high level of performance with a mean accuracy of 97%, making it a competitive model in this research.

```
### Logistic Regression: Training, Cross-Validation, and Testing ###

Performing 5-fold cross-validation...
Cross-validation scores: [0.99590409 0.99667207 0.99556238 0.99615975 0.9958184 ]
Mean CV score: 0.9960 (+/- 0.0008)

Evaluating on the training set...
Training Accuracy: 0.9897

Evaluating on the test set...
Test Accuracy: 0.9703

Detailed Classification Report:

Confusion Matrix:
[[26039   552]
 [  608 11864]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.98      0.98      0.98     26591
         1.0       0.96      0.95      0.95     12472

    accuracy                           0.97     39063
   macro avg       0.97      0.97      0.97     39063
weighted avg       0.97      0.97      0.97     39063


Logistic Regression training, cross-validation, and evaluation completed.
```

Report. 1 - Logistic Regression Classification Report

B. Support Vector Machine (SVM):

SVM was applied for its robustness in handling high-dimensional spaces, particularly for datasets with a clear margin of separation between classes. The SVM model was optimized through hyperparameter tuning, yielding a test accuracy of 96.9%. This model demonstrated its capability in distinguishing between fire and non-fire occurrences based on complex feature interactions.

```
Performing 5-fold cross-validation...
Cross-validation scores: [0.99641608 0.99411213 0.99522103 0.99496501 0.99522103]
Mean CV score: 0.9952 (+/- 0.0015)

Evaluating on the training set...
Training Accuracy: 0.9796

Evaluating on the test set...
Test Accuracy: 0.9690

Detailed Classification Report:

Confusion Matrix:
[[25677   914]
 [  296 12176]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.99      0.97      0.98     26591
         1.0       0.93      0.98      0.95     12472

    accuracy                           0.97     39063
   macro avg       0.96      0.97      0.96     39063
weighted avg       0.97      0.97      0.97     39063


SVM training, cross-validation, and evaluation completed.
```

Report. 2 - Support Vector Machine Classification Report

C. Random Forest:

Random Forest, a robust ensemble method, was selected for its ability to capture nonlinear patterns in the data through its multiple decision trees. The model outperformed others in terms of accuracy, achieving 97.1% after hyperparameter tuning. The feature importance metrics derived from the Random Forest model were instrumental in identifying the most critical predictors of vehicle fire risk, such as fuel type and engine power.

```
### Random Forest: Training, Cross-Validation, and Testing ###

Performing 5-fold cross-validation...
Cross-validation scores: [1. 1. 1. 1. 1.]
Mean CV score: 1.0000 (+/- 0.0000)

Training the Random Forest model on the full training set...

Evaluating on the training set...
Training Accuracy: 1.0000

Evaluating on the test set...
Test Accuracy: 0.9743

Detailed Classification Report:

Confusion Matrix:
[[26122   469]
 [  534 11938]]

Classification Report:
              precision    recall  f1-score   support

         0.0       0.98      0.98      0.98     26591
         1.0       0.96      0.96      0.96     12472

    accuracy                           0.97     39063
   macro avg       0.97      0.97      0.97     39063
weighted avg       0.97      0.97      0.97     39063


Random Forest training, cross-validation, and evaluation completed.
```

Report. 3 - Logistic Regression Classification Report

D. Ensemble Model:

Ensemble methods combine multiple machine learning models to create a more powerful and accurate prediction model. In this research, a Voting Classifier is used as the ensemble technique, which aggregates predictions from several base models, each contributing its prediction to the final decision. The Voting Classifier supports both hard voting (where the majority prediction wins) and soft voting (where the average of predicted probabilities is used). In this study, soft voting is employed.

1. Model Components

The ensemble consists of three distinct classifiers:

- **Random Forest Classifier**: A robust ensemble method that constructs multiple decision trees and merges them to produce more accurate and stable predictions. Random Forest is chosen for its ability to handle complex relationships and mitigate overfitting by averaging the results of multiple trees.
- **Support Vector Classifier (SVC)**: A classification algorithm that works by finding the optimal hyperplane to maximize the margin between different classes. The SVC is used with probabilistic outputs (probability=True) to contribute to the soft voting mechanism.
- **Logistic Regression**: A simple yet effective linear model used for binary classification. Logistic Regression provides probability estimates, which are leveraged in the soft voting process.

2. Soft Voting

In soft voting, the predicted probabilities from each model (Logistic Regression, SVM, Random Forest) are averaged, and the final prediction is based on the highest average probability. This method is useful in my research because it leverages the strengths of all models, making the overall prediction more reliable. If one model is uncertain, the others can compensate, reducing the risk of errors. This flexibility enhances the accuracy of the ensemble model, which is crucial for predicting vehicle fire occurrences more effectively.

The validation and test confusion matrices demonstrate the outstanding performance of the ensemble model in predicting vehicle fire occurrences. For the validation set (11,719 samples), the model accurately predicted 7,860 non-fire cases and 3,822 fire occurrences, with only 37 false positives and no false negatives, showing its high precision and recall. Similarly, in the test set (39,063 samples), it correctly identified 26,478 non-fire cases and 12,472 fire occurrences, with just 113 false positives. Notably, the absence of false negatives in both sets highlights the model's reliability in detecting actual fires. While there is a slight tendency to over-predict fires (false positives), this occurs at a very low rate. The confusion matrix for the ensemble model is displayed in the figure below.

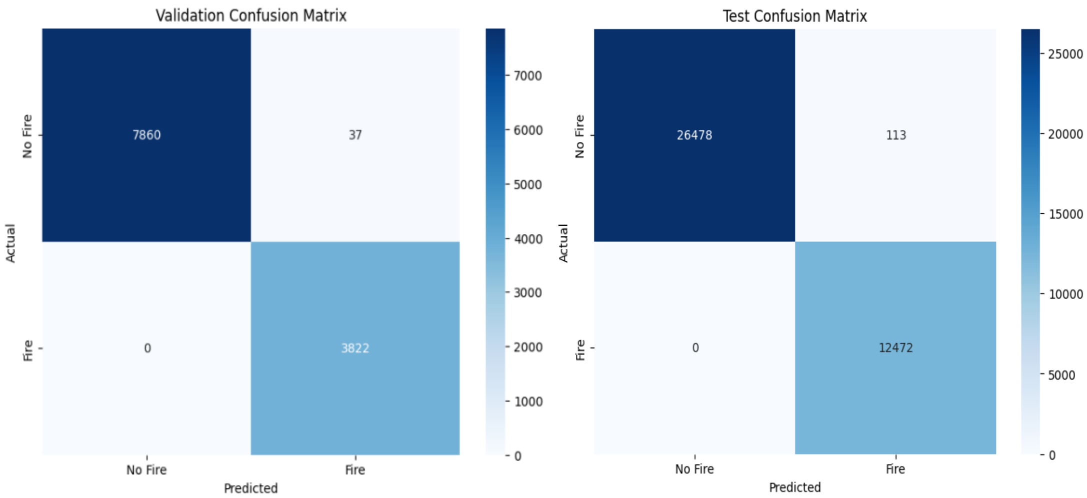

Fig. 3 - Validation and Test Confusion Matrix for ensemble model

6.) IMPLEMENTATION

A. Mathematical Calculations

1. Fire Occurrence Calculation

The synthetic variable `fire_occurrence` is determined using multiple conditions:

$$\boxed{\textbf{fire\_occurrence} = (\text{age\_of\_car}>0.07)\wedge(\text{fuel\_type}\in[\text{'Petrol'},\text{'Diesel'},\text{'CNG'},\text{'Hybrid'}])\wedge(\text{max\_power}>60)\wedge(\text{max\_torque}>90)\wedge(\text{population\_density}>300)\wedge(\text{ncap\_rating}\leq 3)}$$

This Boolean condition defines the fire occurrence, which transforms into a target variable for training.

2. Model Training and Ensemble Voting

The ensemble model combines three classifiers (Random Forest, SVM, and Logistic Regression) using soft voting. In soft voting, the predicted probabilities for each class from the individual models are averaged, and the class with the highest average probability is chosen:

$$\hat{y} = \arg\max \left(\frac{1}{N} \sum_{i=1}^{N} p_i(y) \right)$$

where:

- **pi(y) is the predicted probability of class y from the i-th classifier**
- **N is the number of classifiers.**

3. Accuracy and Confusion Matrix Calculations

Accuracy is calculated as the ratio of correctly predicted instances to the total number of instances:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Population}}$$

The confusion matrix is a 2x2 matrix with values for True Negatives, False Positives, False Negatives, and True Positives. It helps measure model performance for each class:

$$\text{Confusion Matrix} = \begin{pmatrix} TN & FP \\ FN & TP \end{pmatrix}$$

These mathematical formulations are critical for understanding how the model works, from data cleaning and feature extraction to the final prediction.

B. Gradio User Interface (UI)

A Gradio interface was developed to facilitate user interactions, enabling users to input vehicle characteristics and receive immediate predictions along with the probabilities of fire occurrences. This UI enhances accessibility for non-technical users, supporting automotive safety initiatives.

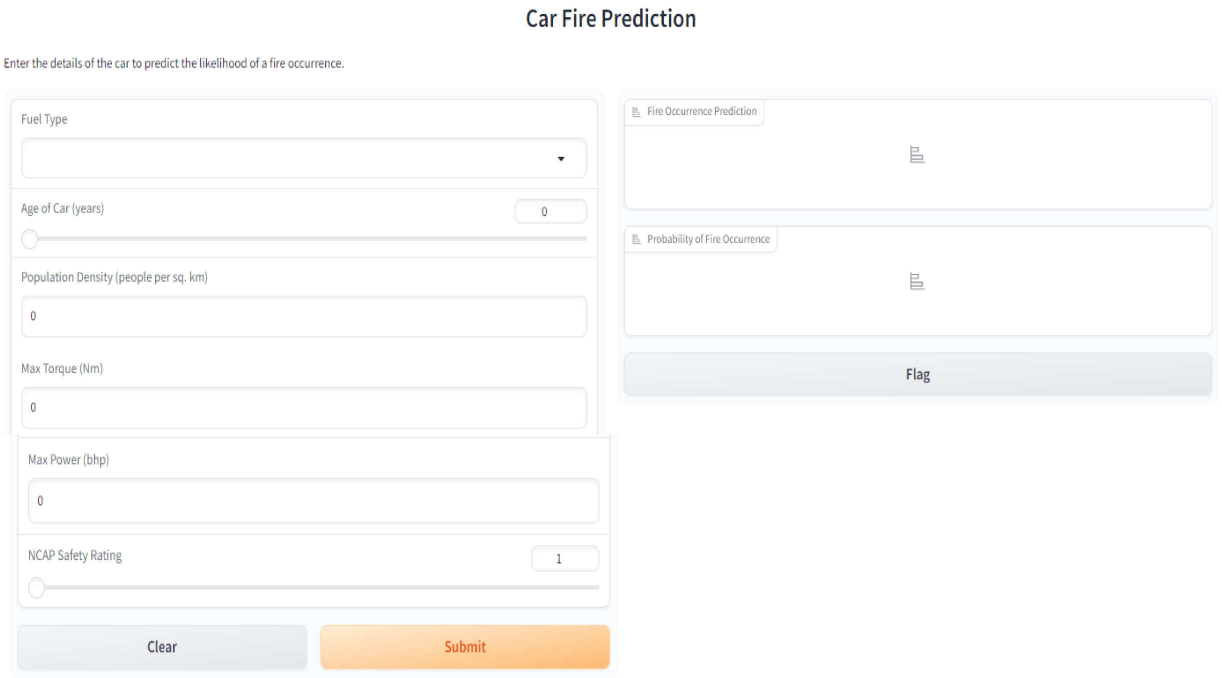

Fig. 4 - Gradio User Interface

C. Predictions

For the given inputs, including age of the car, fuel type, population density, engine power, and NCAP safety ratings, the predictions for fire occurrence are categorized as follows:

- **Outcome**: Yes (Fire Occurrence) / No (No Fire Occurrence)
- **Probability Percentage**

In the figures below, two distinct cases illustrate the predictions made by the model regarding fire occurrences based on various input features.

1. **Figure 5(a)** presents a scenario where a petrol-fueled car, aged 5 years, with a population density of 4000 people per square kilometer, a max torque of 100 Nm, a max power of 150 bhp, and an NCAP safety rating of 4 is assessed. The model predicts **No** for fire occurrence, with a probability of **41.06%**, indicating a lower risk.
2. **Figure 5(b)** details a different situation involving a diesel vehicle that is 15 years old, situated in an area with a high population density of 9000 people per square kilometer. This car has a max torque of 120 Nm, a max power of 200 bhp, and an NCAP safety rating of 1.2. In this case, the model predicts **Yes** for fire occurrence, with a probability of **57.72%**, suggesting a higher risk.

These examples highlight how various vehicle-specific and environmental factors contribute to the model's fire risk predictions, emphasizing the importance of understanding these dynamics for effective safety measures.

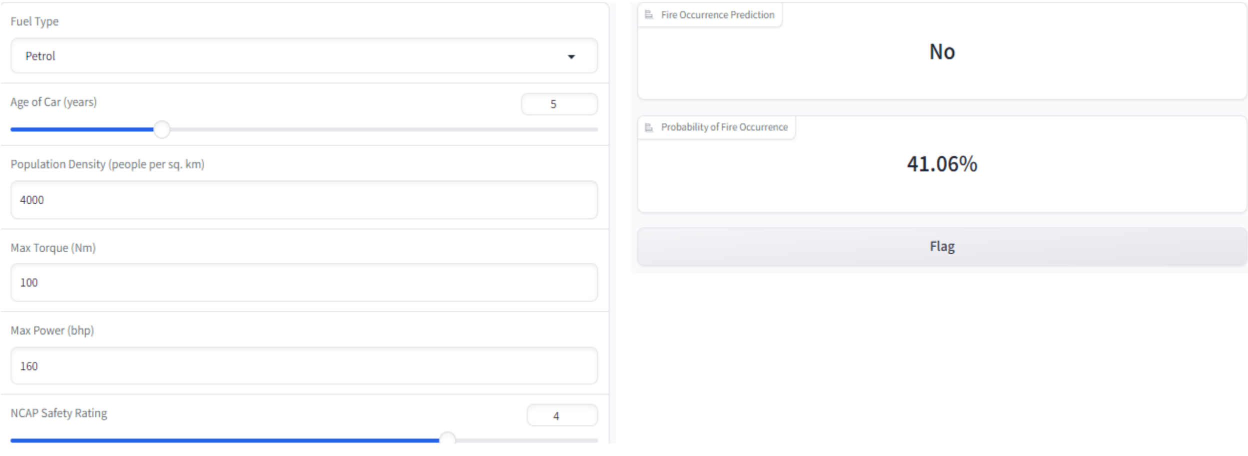

Fig. 5 - (a)Fire Prediction and its probability

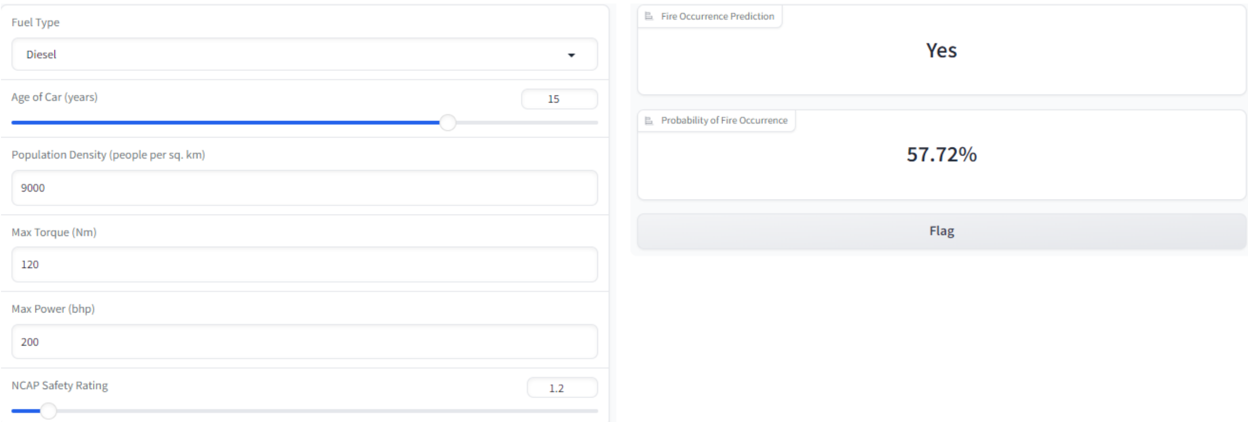

Fig. 5 - (b)Fire Prediction and its probability

7.) RESULTS

The ensemble model, combining Random Forest, Support Vector Classifier, and Logistic Regression, achieved outstanding results with a validation accuracy of 99.68% and a test accuracy of 99.71%. With nearly perfect precision and recall, the model reliably predicts vehicle fire occurrences, minimizing false positives and completely avoiding false negatives.

Metric	Validation Set	Test Set
Accuracy	99.68%	99.71%
Precision (Fire Occ.)	0.99	0.99

Recall (Fire Occ.)	1.00	1.00
F1-Score (Fire Occ.)	0.99	0.99

This high performance makes it highly effective for solving vehicle fire prediction problems, leveraging both linear and complex patterns in the data, making it a robust solution for this critical safety issue.

8.) CONCLUSION

This research highlights how critical factors such as fuel type, engine power, and vehicle age contribute to the risk of car fires. Older vehicles, higher engine outputs, and certain fuel types increase the likelihood of fire due to mechanical wear and increased heat generation. By identifying these risks, the study plays a pivotal role in preventing sudden, unexpected car fires, thus offering an effective approach to safeguarding vehicles and human lives. The findings provide a framework for integrating real-time fire monitoring systems into vehicle safety measures, potentially reducing fire incidents and enhancing automotive safety. This work sets the stage for future advancements in preventing unknown fire hazards.

REFERENCES :

[1] *India Today*, May 19, 2024, "Moving car catches fire at Delhi-Meerut Expressway, driver escapes unhurt"
Referenced from:
https://www.indiatoday.in/india/story/delhi-meerut-highway-car-catches-fire-ghaziabad-heatwave-2541169-2024-05-19

[2] *The New Indian Express*, June 08, 2024, "65-year-old dies after moving car catches fire in Kozhikode"
Referenced from:
https://www.newindianexpress.com/states/kerala/2024/Jun/08/65-year-old-dies-after-moving-car-catches-fire-in-kozhikode

[3] *The Hindu*, August 22, 2024, "Car catches fire near Ambur town on Chennai-Bengaluru Highway"
Referenced from:
https://www.thehindu.com/news/national/tamil-nadu/car-catches-fire-near-ambur-town-on-chennai-bengaluru-highway/article68554382.ece

[4] *The Hindu*, September 03, 2024, "Car catches fire near Katpadi in Vellore"
Referenced from:
https://www.thehindu.com/news/national/tamil-nadu/car-catches-fire-near-katpadi-in-vellore/article68601081.ece

[5] Li, Zhichen & Qin, Zhao & Luo, Weiping & Ling, Xiujun. (2024). Gasoline Engine Misfire Fault Diagnosis Method Based on Improved YOLOv8. Electronics. 13. 2688. 10.3390/electronics13142688.

[6] Hassan, Md Kamrul & Hameed, Nazra & Hossain, Delwar & Hasnat, Md Rayhan & Douglas, Grahame & Pathirana, Sameera & Rahnamayiezekavat, Payam & Saha, Swapan. (2023). Fire Incidents, Trends, and Risk Mitigation Framework of Electrical Vehicle Cars in Australia. Fire. 6. 325. 10.3390/fire6080325.

[7] Mohd Tohir, Mohd Zahirasri & Spearpoint, Michael & Fleischmann, Charles. (2020). Probabilistic design fires for passenger vehicle scenarios. Fire Safety Journal. 120. 103039. 10.1016/j.firesaf.2020.103039.

[8] Boehmer, Haavard & Klassen, Michael & Olenick, Stephen. (2020). Modern Vehicle Hazards in Parking Structures and Vehicle Carriers.

[9] Choi, Myoung-Young & Jun, Sunghae. (2020). Fire Risk Assessment Models Using Statistical Machine Learning and Optimized Risk Indexing. Applied Sciences. 10. 4199. 10.3390/app10124199.

[10] Mohd Tohir, Mohd Zahirasri & Spearpoint, Michael. (2019). Probability of Fire Spread Between Vehicles in Car Parking Buildings. 10.1007/978-981-10-8016-6_97.

[11] Surya, Lakshmisri. (2017). Risk Analysis Model That Uses Machine Learning to Predict the Likelihood of a Fire Occurring at A Given Property. SSRN Electronic Journal. 5. 959. 10.1729/Journal.25787.

[12] Jiang, Xiao-hui & Zhu, Guo-qing & Zhu, Hui & Li, Da-yan. (2018). Full-scale Experimental Study of Fire Spread Behavior of Cars. Procedia Engineering. 211. 297-305. 10.1016/j.proeng.2017.12.016.