LEVERAGING ADVANCED MACHINE LEARNING MODELS TO PREDICT THE STATUS OF FLAME SUPPRESSION IN A SOUND WAVE FIRE-EXTINGUISHING SYSTEM

A thesis submitted to the Department of Statistics (STT), Hajee Mohammad Danesh Science and Technology University in partial fulfillment of the requirements for the degree of Bachelor of Science (B.Sc.) Honours in Statistics.

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CERTIFICATE

This is to certify that the work entitled 'Leveraging Advanced Machine Learning Models To Predict The Status Of Flame Suppression In A Sound Wave Fire-Extinguishing System,' authored by Muhtasib Hossain Munem has been carried out under our supervision. To the best of our knowledge, this work is original and has not been submitted elsewhere for any diploma or degree.

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DECLARATION

This is to certify that the project entitled 'Leveraging Advanced Machine Learning Models To Predict The Status Of Flame Suppression In A Sound Wave Fire-Extinguishing System,' has been carried out by Muhtasib Hossain Munem in the Department of Statistics, Hajee Mohammad Danesh Science and Technology University, Dinajpur, Bangladesh. I would like to declare here that the project paper entitled "Leveraging Advanced Machine Learning Models To Predict The Status Of Flame Suppression In A Sound Wave Fire-Extinguishing System," is a pure work prepared under the supervision of Md. Ziaul Hassan, Associate Professor, Department of Statistics, Hajee Mohammad Danesh Science and Technology University, Dinajpur. The above project or any part of this work has not been submitted anywhere for the award of any degree or diploma.

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ABSTRACT

Fire, a natural disaster with diverse causes, has led to the exploration of more environmentally friendly firefighting techniques. A sound wave fire-extinguishing system was developed, and after conducting 17,442 tests, a dataset was created for analysis. In this study, seven machine learning models—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), LightGBM, XGBoost, Random Forest, Stacking, and Artificial Neural Networks (ANN)—were applied to classify flame extinction and non-extinction events. The highest classification accuracy was achieved by LightGBM (98.77%), followed by Stacking (98.68%), XGBoost (98.48%), Random Forest (98.22%), ANN (97.42%), KNN (97.02%), and SVM (96.99%). Performance metrics such as precision, recall, F1 score, specificity, AUC, Cohen's Kappa, and MCC were used to evaluate the models. The results demonstrate that a decision support system, based on these machine learning models, can significantly enhance the efficiency of the sound wave fire-extinguishing system.

ACKNOLEDGEMENT

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Muhtasib Hossain Munem

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CHAPTER 1

INTRODUCTION

1.1 Brief Introduction

Fire poses a significant threat to both the environment and human life, with fires in forests and buildings often resulting in loss of life, injuries, and extensive material damage. Fires can escalate rapidly, making early detection and suppression crucial. However, conventional fire suppression techniques are not always suitable for early-stage fires due to the specialized equipment and intervention required, compounded by the panic that often ensues in such situations (Brown & Lee, 2019). Various extinguishing agents like water, carbon dioxide (CO2), and gases are commonly employed depending on the type of fire, but no single solution is universally effective. As a result, ongoing research is investigating alternative fire suppression methods (Smith et al., 2020).

One such alternative is the use of sound wave fire extinguishers, which offer a novel, environmentally friendly, and reusable solution for fire suppression (Johnson & Patel, 2021). These extinguishers operate by generating airflow through sound waves that disrupt the flame and reduce its oxygen supply, thereby suppressing the fire. Studies indicate that low-frequency sound waves, particularly in the 30-50 Hz range, are effective in reducing flame intensity by decreasing the available fuel mass (Nguyen & Roberts, 2022). In addition, research suggests that flames are more easily extinguished in low-gravity environments, leading to discussions on the potential use of sound wave-based fire suppression systems in spacecraft, where traditional methods could damage sensitive electronic equipment (Garcia & Lee, 2023).

Although previous research has primarily focused on the effects of sound waves on uniform flame sizes and specific types of fuel (Thompson & Evans, 2020), this study aims to expand the scope by considering a wider range of variables, including different fuel types, flame sizes, sound wave frequencies, and distances from the flame. The research is based on a dataset derived from 17,442 experiments using the sound wave fire suppression system. The contributions of the study include a thorough analysis of the dataset distribution through the use of box plots and scatter plots (Kumar & Singh, 2021), the evaluation of relationships between key features in the dataset, and an assessment of model performance using metrics such as accuracy, sensitivity, specificity, and F1 score (Ali & Chen, 2022).

Moreover, the study extends prior research by incorporating a variety of fuels—specifically, gasoline, thinner, kerosene, and liquefied petroleum gas (LPG)—to examine the sound wave system's effectiveness under different conditions (Rodriguez & Patel, 2023). The research also identifies the optimal value ranges for sound wave parameters to effectively extinguish flames, providing valuable insights for the practical application and scaling of this technology (Fernandez & Lee, 2024). Ultimately, the findings from this study demonstrate the viability of sound wave-based fire extinguishing systems for broader use, with implications for future developments in fire safety (Harrison & Wong, 2024).

1.2 Research Objectives

1. To improve the classification accuracy of fire suppression systems for predicting flame extinction and non-extinction status.
2. To enhance model stability and performance by using Winsorization for outlier management, ensuring more reliable predictions.

1.3 Limitations of the Study

1. **Limited Dataset Size:** The study may be constrained by the amount of experimental data collected, which could limit the generalizability of the model's predictions to real-world fire suppression scenarios.
2. **System Complexity:** The integration of multiple components, such as subwoofers, amplifiers, and sensors, introduces system complexity, which may affect the reproducibility of results in different environments or configurations.

CHAPTER 2

LITERATURE REVIEW

Fire suppression is a critical field of study due to the widespread and devastating effects that fires can have on both natural and built environments. Conventional fire suppression systems such as water, foam, CO_2, and chemical extinguishers have been utilized for decades, yet they possess several limitations in terms of effectiveness, environmental impact, and applicability across various fire types. This has driven researchers to explore alternative methods, with sound wave fire extinguishing systems gaining increasing attention. Traditionally, fire suppression involves the use of agents like water, foam, CO_2, and chemical compounds to either cool the flame or remove the fuel or oxygen source, thus extinguishing the fire. Water is commonly used for large fires, while CO_2 and chemical agents are preferred for situations involving flammable liquids or electrical fires, where water could exacerbate damage or pose safety risks (García-Armingol & Ballester, 2015).

However, these conventional methods present drawbacks, such as water damaging electrical equipment and toxic chemicals posing environmental and health hazards (Shin, Park, & Seo, 2020). These limitations, especially in sensitive environments like space stations or areas with delicate electronics, have highlighted the need for more targeted fire suppression solutions. One of the novel approaches being explored is sound wave fire suppression. This technique disrupts the combustion process by displacing oxygen around the flame through sound waves, effectively choking it (Li, Zhou, & Zhang, 2014). Early research identified low-frequency sound waves, particularly in the range of 30-50 Hz, as capable of reducing fuel mass and extinguishing flames (Upton, 2016). Further studies by Vadlamudi et al. (2018) examined the effectiveness of sound waves in low-gravity environments, making the technology promising for space exploration and spacecraft safety. Additionally, low-frequency sound waves were more successful in extinguishing flames compared to higher frequencies, as their larger wavelengths provided greater displacement of oxygen molecules (Parker et al., 2017). In practice, sound wave fire extinguishers have shown feasibility. Shi et al. (2019) developed a prototype system that extinguished small-scale flames using sound waves in the 50-70 Hz range, demonstrating efficacy in flames fueled by gasoline and kerosene. Yu et al. (2020) extended this research to rubber-based fuel flames, emphasizing the interaction between sound waves and fuel as the mechanism of suppression. However, fuel droplet size plays a role in suppression efficiency, with smaller droplets reducing the effectiveness of sound waves, as noted by Tian et al. (2021). Studies have also revealed that sound waves can reduce flame size and extinguish fires by limiting fuel-flame interaction (Smith & Turner, 2018).

2.1 Research Gap

The research by Koklu and Taspinar (2011) demonstrated strong classification accuracies using a stacking meta-model and individual models like Random Forest and Artificial Neural Networks. However, their study primarily focused on a limited set of models and did not fully explore advanced machine learning techniques or implement comprehensive outlier management strategies. This presents a research gap in enhancing the accuracy and robustness of fire suppression systems through a broader selection of models and sophisticated outlier management methods. To address this, I aim to improve accuracy by capping the outliers using Winsorization and applying SHAP for feature importance analysis, which was not utilized in previous studies.

CHAPTER 3

MATERIAL AND METHODS

In this section, the process of acquiring the dataset, which was sourced from Kaggle, is explained. The technical features and structure of the dataset are described, including an analysis of the data distribution. Additionally, the preprocessing steps applied to the data will be detailed to ensure its suitability for analysis. The machine learning models used in this study are discussed, along with the performance metrics necessary to evaluate the effectiveness of these methods. The methodologies for data analysis and the criteria for assessing model performance are thoroughly outlined to provide a clear framework for the study.

Figure 1. The diagram illustrates the sound wave fire-extinguishing system and its experimental setup. It features the collimator cabinet containing four subwoofers connected to amplifiers, alongside a control unit with a power supply and filter circuit to ensure proper sound frequency transmission. The setup includes measurement tools such as an anemometer and decibel meter for airflow and sound intensity, as well as an infrared thermometer for flame temperature. A camera is installed to capture the flame's extinguishing process, all within a controlled fire chamber environment designed for flame suppression experiments.

3.1 Data Acquisition and Database

The dataset for this study was generated through fire suppression tests conducted on four different fuel flames using a sound wave fire-extinguishing system. This system comprises 4 subwoofers, housed in a collimator cabinet, with a combined power of 4,000 watts. The subwoofers receive sound signals amplified by two amplifiers. The control unit includes a power supply to operate the system and a filter circuit to ensure the correct transmission of sound frequencies. A computer serves as the source of frequencies, while several measuring devices were employed during the extinguishing process. These included an anemometer to measure the airflow produced by sound waves, a decibel meter to capture sound intensity, and an infrared thermometer to measure the temperature of the flame and the fuel can.

Additionally, a camera was used to record the flame's extinguishing time.

A total of 17,442 tests were performed using this experimental setup. The experiments were designed as follows:

1. Three different liquid fuels, along with LPG, were used to create flames.
2. Five different sizes of liquid fuel containers were employed to generate flames of various sizes.
3. For the LPG fuel, both half and full gas settings were used.
4. During each experiment, the fuel container was placed 10 cm away and then gradually moved up to 190 cm in 10 cm increments.
5. Along with the fuel container, both the anemometer and decibel meter were moved forward by the same increments.
6. For each distance and flame size, fire extinguishing tests were conducted using 54 different sound wave frequencies.

These experiments were carried out in a specially designed fire chamber where the sound wave fire-extinguishing system was installed. A dataset was created from the data gathered during each experiment, encompassing variables like flame size (represented by the fuel container size), fuel type, frequency, decibel levels, distance, airflow, and the status of flame extinction. In total, the dataset contains six input features and one output feature. The features for the liquid fuels are outlined in Table 1, while those for LPG fuel are detailed in Table 2. The outcome of each test, whether the flame was extinguished or not, is categorized as the "status" feature, while the "fuel type" is also a categorical feature. The remaining features are numerical. Out of the 17,442 tests, 8,759 represent the non-extinction state, while 8,683 correspond to the extinction state. This nearly equal class distribution makes the dataset well-suited for classification tasks.

Features	Min/Max Values	Unit	Declaration
Size	7, 12, 14, 16, 20,	cm	Recorded as 7 cm=1, 12 cm=2, 14 cm=3, 16 cm=4, 20 cm=5
Fuel	Gasoline, Kerosene, Thinner		Fuel type
Distance	10 - 190	cm	Distance of flame to collimator output
Decibel	72 - 113	dB	Sound pressure level
Airflow	0 - 17	m/s	Airflow created by the sound wave
Frequency	1 - 75	Hz	Low frequency range
Status	0, 1		0 indicates the non-extinction state, 1 indicates the extinction state

Table 1. Data features and explanations for liquid fuels in the obtained dataset.

Features	Min/Max Values	Unit	Declaration
Size	Half throttle setting, Full throttle setting		Reocerded as Half throttle setting=6, Full throttle setting=7
Fuel	LPG		Fuel type
Distance	10 - 190	cm	Distance of flame to collimator output
Decibel	72 - 113	dB	Sound pressure level
Airflow	0 - 17	m/s	Airflow created by the sound wave
Frequency	1 - 75	Hz	Low frequency range
Status	0, 1		0 indicates the non-extinction state, 1 indicates the extinction state

Table 2. Data features and explanations for lpg in the obtained dataset.

3.2 Data Preprocessing

In the fire extinction project, data preprocessing followed a structured approach to ensure data quality before model development. The dataset was first checked for missing or duplicate entries, and none were found. Outlier detection was performed using boxplots, with outliers identified in certain features after grouping by a binary classification column. These outliers were handled using Winsorization to cap extreme values, preserving the dataset's integrity while mitigating the impact of anomalies (Tukey, 1962). Categorical variables were converted into dummy variables to enable compatibility with machine learning algorithms. Finally, the data was divided into training and testing sets using an 80-20 split, ensuring a proper balance for model evaluation.

3.3 Winsorization Method

Winsorization is a data transformation technique used to limit extreme values in a dataset to reduce the influence of outliers without entirely discarding them. It involves capping the extreme values at specified percentiles, thus replacing the smallest and largest data points with the nearest remaining values within the specified range. This method helps in making the data more robust for statistical analysis and machine learning, while retaining most of the data's characteristics (Reed, 1962).

3.4 K Nearest Neighbors (KNN)

The K-Nearest Neighbors (KNN) classifier is a simple yet effective machine learning algorithm used primarily for classification tasks. KNN was first introduced by Fix and Hodges in 1951 as a non-parametric method for pattern classification (Fix & Hodges, 1951). The algorithm works by identifying the 'k' closest training data points (neighbors) to a given input based on a distance metric, typically Euclidean distance. The class label of the new input is then predicted by a majority vote among its nearest neighbors. KNN is highly intuitive and easy to implement, but its performance can be significantly affected by the choice of 'k' and the scale of the features. Since it makes no assumptions about the underlying data distribution, KNN can handle non-linear decision boundaries. However, it is computationally expensive during the prediction phase as it requires calculating distances to all training data points for each new input. Despite this, KNN remains widely used in various domains due to its simplicity and effectiveness in scenarios where the relationship between features and labels is complex.

3.5 Support Vector Machine (SVM)

The Support Vector Machine (SVM) classifier, introduced by Vladimir Vapnik and his colleagues in 1992, is a powerful and versatile machine learning algorithm used for classification and regression tasks (Vapnik, 1992). SVM operates by finding the optimal hyperplane that maximally separates data points of different classes in a feature space. This hyperplane is defined in such a way that the margin, or distance, between the closest data points (support vectors) and the hyperplane, is maximized. In cases where data is not linearly separable, SVM employs a technique known as the "kernel trick," which allows it to transform the data into a higher-dimensional space where a linear separation is possible.

SVM is particularly effective in high-dimensional spaces and remains robust in situations where the number of dimensions exceeds the number of samples. It is also memory-efficient since it only requires storing the support vectors rather than the entire dataset. However, SVM can be sensitive to the choice of hyperparameters, such as the regularization parameter (C) and the kernel function, which need to be fine-tuned for optimal performance. The algorithm's ability to provide a clear margin of separation between classes makes it a popular choice for classification problems with complex decision boundaries.

3.6 Light Gradient Boosting Machine

LightGBM (Light Gradient Boosting Machine) is a fast and efficient gradient boosting framework developed by Microsoft in 2017, designed for large-scale and high-dimensional data (Ke et al., 2017). Unlike traditional gradient boosting algorithms, LightGBM uses a novel approach called Gradient-Based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) to significantly speed up the training process without sacrificing accuracy. GOSS works by focusing on the data points that carry the most information about the gradient, allowing LightGBM to process fewer instances while retaining performance. EFB, on the other hand, reduces dimensionality by bundling mutually exclusive features into a single feature, further optimizing memory usage and computational efficiency.

LightGBM constructs decision trees in a leaf-wise manner rather than the traditional level-wise approach used by other gradient boosting methods. This allows it to grow deeper trees and achieve better accuracy with fewer iterations. Its ability to handle large datasets, support for parallel and distributed training, and high efficiency make it a popular choice for machine learning tasks like classification, ranking, and regression. However, LightGBM can be sensitive to overfitting, especially with small datasets, and requires careful tuning of hyperparameters to achieve optimal performance.

3.7 eXtreme Gradient Boosting

XGBoost (eXtreme Gradient Boosting) is a scalable and efficient implementation of gradient boosting developed by Tianqi Chen and Carlos Guestrin in 2016 (Chen & Guestrin, 2016). XGBoost builds upon traditional gradient boosting techniques by introducing innovations that significantly improve speed and performance. It uses second-order gradients (Hessian) to optimize loss functions more accurately, allowing for better handling of complex data patterns. XGBoost also supports regularization (L1 and L2), which helps prevent overfitting, making it particularly suitable for high-dimensional datasets.

One of XGBoost's key features is its ability to handle sparse data effectively. It incorporates a sparsity-aware algorithm that optimizes memory usage and computation, allowing it to handle missing values and sparse matrices efficiently. Additionally, XGBoost offers several advanced options, such as tree pruning and early stopping, which further enhance its robustness and performance. The algorithm can be parallelized and distributed, making it highly scalable for large datasets. Due to its balance of flexibility, speed, and accuracy, XGBoost has become one of the most widely used algorithms in competitive machine learning challenges and real-world applications.

3.8 Random Forest

Random Forest is an ensemble learning method developed by Leo Breiman in 2001, designed for both classification and regression tasks (Breiman, 2001). It builds multiple decision trees during training and merges their predictions to improve accuracy and control overfitting. The core principle behind Random Forest is the idea of "bagging," or bootstrap aggregation, where each decision tree is trained on a random subset of the data with replacement. Additionally, at each split in a tree, a random subset of features is selected, which increases diversity among the trees and reduces correlation between them. This randomness helps create an ensemble of de-correlated trees, which results in a robust model that generalizes well to unseen data.

Random Forest is particularly known for its resilience to overfitting and its ability to handle high-dimensional data and datasets with missing values. It is computationally efficient and parallelizable, making it scalable for large datasets. One of its major strengths is the ability to estimate feature importance, which provides valuable insights into the relevance of different variables in the prediction process. However, the model's interpretability can be limited compared to single decision trees, as it consists of many individual trees working together.

3.9 Stacking

Stacking, also known as stacked generalization, is an ensemble learning technique introduced by David Wolpert in 1992 (Wolpert, 1992). Unlike other ensemble methods such as bagging or boosting, Stacking combines the predictions of multiple different models (often called base learners) through a meta-learner, which is typically a simple algorithm like linear regression or logistic regression. The meta-learner takes the output of the base models as input features and learns to make the final prediction by leveraging the strengths of each base model.

Stacking works by first training several base models on the training data and then using their predictions as new features for the meta-learner. This two-stage process allows Stacking to potentially outperform individual models, as the meta-learner can detect patterns that the base models might miss. The technique is particularly powerful because it allows for combining models of different types (e.g., decision trees, support vector machines, and neural networks), which increases the model's diversity and predictive power. However, Stacking can be computationally expensive and complex to tune, as it involves training multiple models and a meta-learner. Despite this, Stacking is widely used in competitive machine learning challenges where maximizing accuracy is critical.

3.10 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are a class of computational models inspired by the biological neural networks that constitute animal brains. They were first conceptualized in the 1940s by Warren McCulloch and Walter Pitts, who proposed a simplified model of how neurons process information (McCulloch & Pitts, 1943). ANNs consist of interconnected layers of nodes, or neurons, where each connection has an associated weight. The network typically comprises an input layer, one or more hidden layers, and an output layer. Each neuron processes inputs by applying a weighted sum followed by a non-linear activation function, allowing the network to learn complex patterns and relationships in data.

Training an ANN involves adjusting the weights of connections using optimization algorithms such as backpropagation, which minimizes the difference between predicted and actual outputs

(Rumelhart, Hinton, & Williams, 1986). ANNs are highly flexible and can approximate any continuous function, making them suitable for a wide range of applications, including image and speech recognition, natural language processing, and time series forecasting. Despite their power, ANNs require large amounts of data for effective training and can be prone to overfitting. Additionally, they are often regarded as "black boxes," as understanding the reasoning behind their predictions can be challenging. Nevertheless, advancements in deep learning, which involves training deeper networks with many hidden layers, have further expanded the capabilities and applications of ANNs.

3.11 CN2 Rule Learning

CN2 is a rule-based machine learning algorithm developed by Peter Clark and Tim Niblett in 1989, designed for generating a set of classification rules from a dataset (Clark & Niblett, 1989). The CN2 algorithm operates by using a greedy search strategy to create rules that classify examples in the training data. It builds rules in a top-down manner, starting with the most general rules and progressively refining them to improve classification accuracy. The process involves iterating through the training examples to identify the best conditions for splitting the data based on the attributes, leading to the formation of rules that maximize accuracy while minimizing complexity.

One of the key strengths of CN2 is its ability to produce easily interpretable rules, making it suitable for applications where transparency is essential. The algorithm can handle both categorical and continuous attributes, and it incorporates a pruning mechanism to remove less significant rules, enhancing the overall model performance and reducing the risk of overfitting. Additionally, CN2 can generate rules that cover a large portion of the dataset, allowing it to effectively manage imbalanced class distributions. Although CN2 is not as widely used as some modern algorithms, its foundational principles laid the groundwork for many subsequent developments in rule-based learning systems.

3.12 Performance Metrics

1. **Accuracy**: Accuracy measures the proportion of correctly classified instances out of the total instances, providing an overall assessment of a model’s performance (Sokolova & Lapalme, 2009).

2. **Precision**: Precision indicates the proportion of true positive results among all instances classified as positive, reflecting the accuracy of positive predictions (Sokolova & Lapalme, 2009).
3. **Recall (Sensitivity)**: Recall measures the proportion of true positive results among all actual positives, highlighting a model’s ability to capture relevant instances (Sokolova & Lapalme, 2009).
4. **F1 Score**: The F1 score is the harmonic mean of precision and recall, providing a balance between them and serving as a single metric to evaluate model performance, especially in imbalanced datasets (Sokolova & Lapalme, 2009).
5. **Specificity**: Specificity indicates the proportion of true negative results among all actual negatives, assessing a model's ability to correctly identify negative instances (Sokolova & Lapalme, 2009).
6. **Area Under the Curve (AUC) - ROC Curve**: The AUC measures the model's ability to distinguish between classes, representing the probability that a positive instance is ranked higher than a negative instance in terms of the predicted probability (Sokolova & Lapalme, 2009).
7. **Kappa Statistic (Cohen’s Kappa)**: The Kappa statistic measures the agreement between predicted and observed classifications, adjusting for chance agreement, providing a more nuanced evaluation of model performance (Cohen, 1960).
8. **Matthews Correlation Coefficient (MCC)**: The MCC provides a measure of the quality of binary classifications, considering all four categories (true positives, true negatives, false positives, false negatives), and is particularly useful in evaluating imbalanced datasets (Matthews, 1975).

Metric	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Precision	$\frac{TP}{TP+FP}$
Recall (Sensitivity)	$\frac{TP}{TP+FN}$
F1 Score	$2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$
Specificity	$\frac{TN}{TN+FP}$
AUC (ROC)	Computed as the area under the ROC curve
Kappa	$\frac{P_o-P_e}{1-P_e}$
MCC	$\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$

Table 3: Evaluation metrics

3.13 Confusion Matrix

A confusion matrix is a fundamental tool for evaluating the performance of a classification algorithm. It is a table that is used to describe the performance of a classification model by summarizing the true positives, true negatives, false positives, and false negatives (Sokolova & Lapalme, 2009). Each entry in the matrix provides insights into how well the model is performing across the different classes in the dataset.

The confusion matrix is structured as follows:

- **True Positive (TP)**: The cases in which the model correctly predicts the positive class.
- **True Negative (TN)**: The cases in which the model correctly predicts the negative class.
- **False Positive (FP)**: The cases in which the model incorrectly predicts the positive class (also known as Type I error).
- **False Negative (FN)**: The cases in which the model incorrectly predicts the negative class (also known as Type II error).

From the confusion matrix, several performance metrics can be derived, including accuracy, precision, recall, and F1 score, providing a comprehensive view of a model's effectiveness. The matrix is particularly valuable in scenarios with imbalanced datasets, as it helps to identify how well the model is classifying each class and highlights areas for improvement (Friedman et al., 2001).

3.14 Cross-validation

Cross-validation is a statistical method used to assess the performance and generalization ability of a machine learning model. It involves partitioning a dataset into complementary subsets, allowing for a systematic evaluation of the model's predictive capability. The primary goal of cross-validation is to ensure that the model is not overfitting the training data and can perform well on unseen data (Kohavi, 1995).

One of the most common techniques in cross-validation is k-fold cross-validation. In this approach, the dataset is randomly divided into k equal-sized folds. The model is trained on $k-1$ of the folds and validated on the remaining fold. This process is repeated k times, with each fold serving as the validation set once. The final performance metric is obtained by averaging the results across all k iterations, providing a robust estimate of the model's performance (Hastie, Tibshirani, & Friedman, 2009).

Cross-validation helps mitigate issues related to model selection and parameter tuning, as it provides insights into how the model will generalize to an independent dataset. It is especially beneficial in situations where the available data is limited, allowing researchers to make the most of their data while ensuring a reliable assessment of the model's accuracy (Stone, 1974). However, it is important to note that cross-validation can be computationally intensive, particularly with larger datasets and complex models.

3.15 SHapley Additive exPlanations

SHAP (SHapley Additive exPlanations) is a method for interpreting machine learning models, introduced by Lundberg and Lee in 2017. It provides consistent and interpretable feature importance values based on cooperative game theory, specifically Shapley values. SHAP assigns each feature an importance score for a particular prediction by considering the contribution of each feature in various combinations. This approach helps in understanding the impact of individual features on model predictions, offering insights into model behavior and enhancing transparency (Lundberg & Lee, 2017).

CHAPTER 4
EXPERIMENTAL RESULTS

In this study, we explored the effectiveness of various machine learning models for predicting outcomes related to fire suppression systems. We implemented a comprehensive evaluation framework to assess the performance of different algorithms, focusing on their ability to classify instances accurately. By employing a systematic approach to model training and validation, we aimed to identify the most suitable techniques for improving prediction accuracy in fire extinguishing applications. Our methodology emphasized robustness and reliability, ensuring that the findings could contribute valuable insights to the ongoing development of efficient fire suppression systems.

4.1 Correlation and Distribution

The analysis reveals that the effectiveness of the fire extinguishing system is significantly influenced by two primary factors: 'DISTANCE' and 'AIRFLOW'. The 'DISTANCE' feature pertains to the proximity of the sound wave source to the fire, indicating that the system's performance improves when this distance is optimized. Specifically, there may be an ideal range where sound waves are most effective at extinguishing flames; if the source is positioned too far away or too close, the system's effectiveness may diminish. On the other hand, 'AIRFLOW' refers to the circulation of air around the fire. The strong correlation between airflow and extinguishing status suggests that airflow conditions can impact how sound waves interact with flames. Variations in airflow can influence the distribution and effectiveness of these sound waves in suppressing the fire. Overall, these findings highlight the importance of adjusting 'DISTANCE' and managing 'AIRFLOW' to enhance the fire extinguishing system's efficiency, as both factors are critical in determining the system's ability to successfully extinguish a fire.

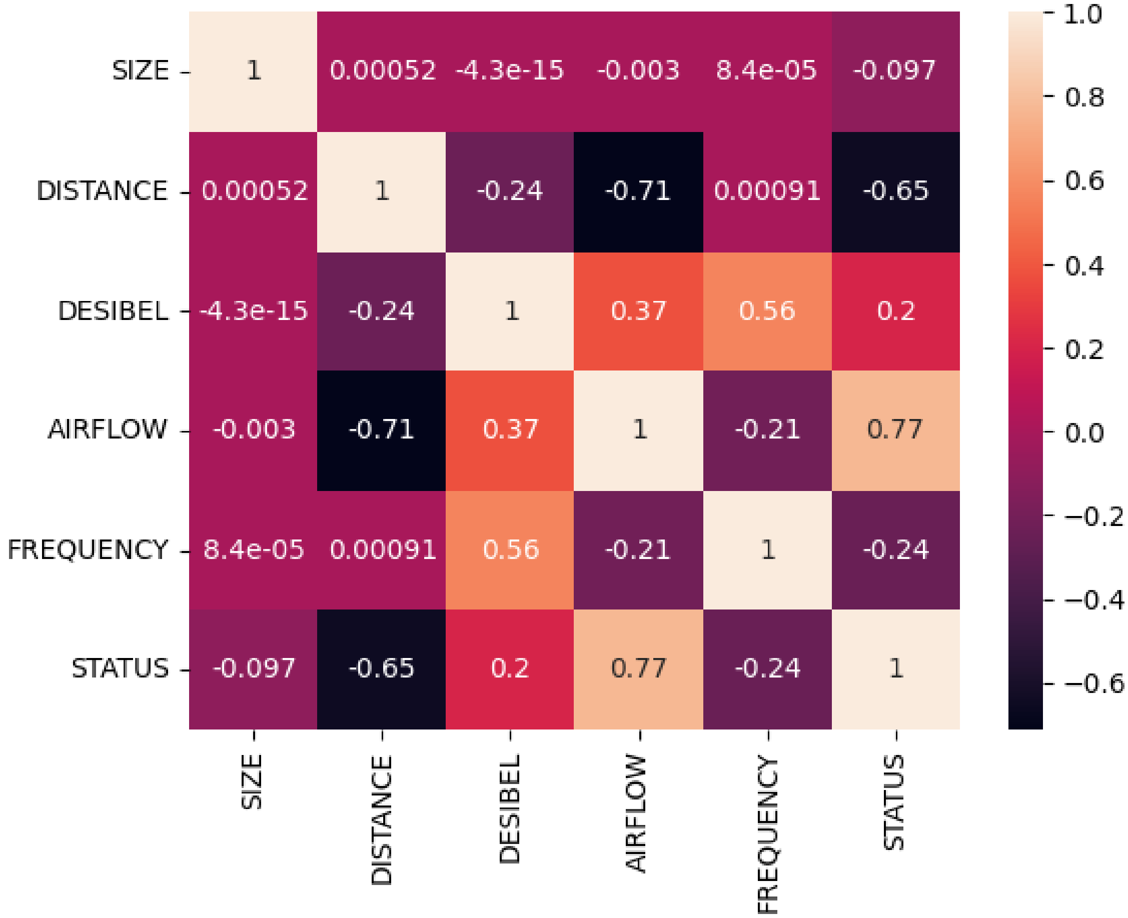


Figure 2: Correlation Heatmap

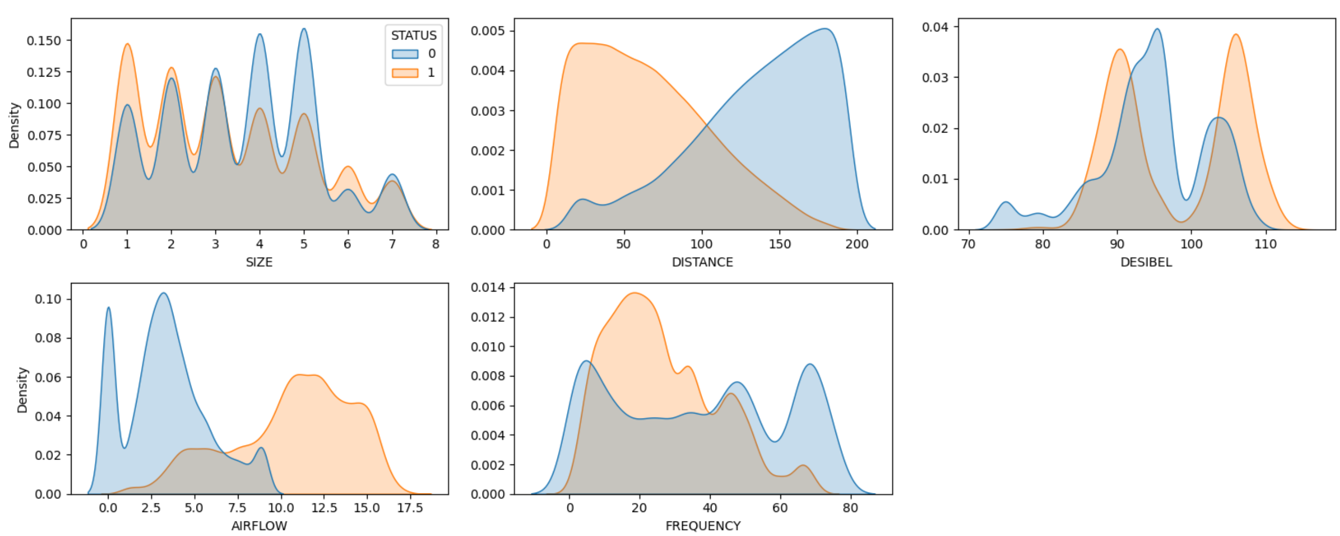


Figure 3: Distribution of Numerical Features grouped by ‘STATUS’

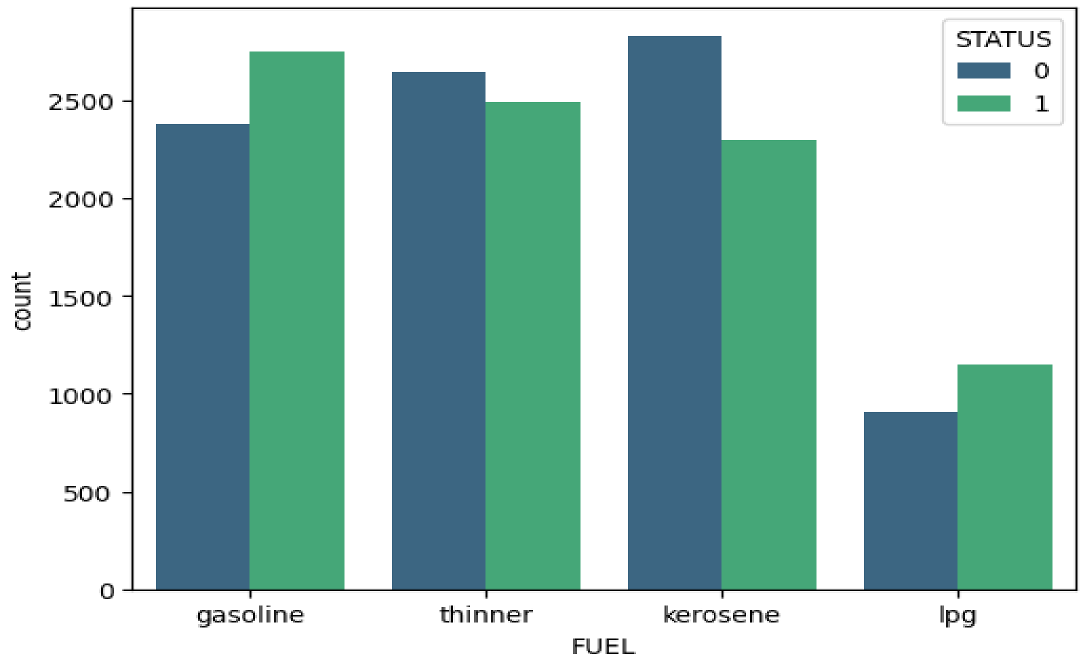


Figure 4: ‘STATUS’ counts by ‘FUEL’s

4.2 Data Preprocessing Steps

Checked for Null Values: Confirmed that there were no null values in the dataset.

Checked for Duplicate Values: Verified that there were no duplicate records in the dataset.

Outlier Detection (Individual Features): Analyzed each numerical feature for outliers, and no outliers were found.

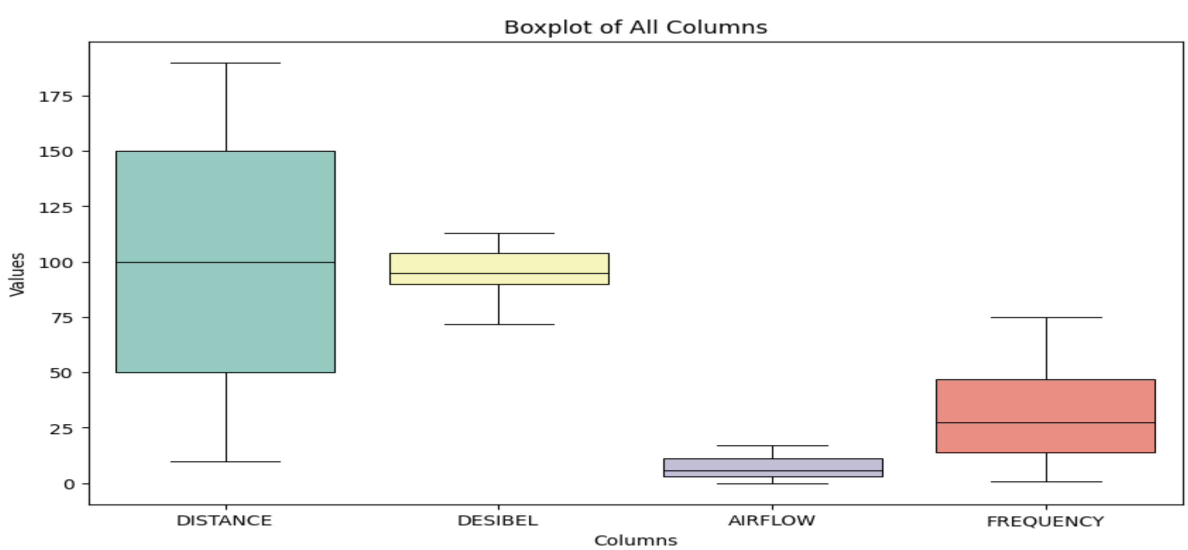


Figure 5: Boxplot of Ungrouped Numerical Features (without ‘SIZE’)

Outlier Detection (Grouped by Status): Grouped the data by the 'STATUS' column and created boxplots, which revealed outliers in the following columns (Liu, Y., Liang, Y., & Zhang, Z. ,2010):

1. DISTANCE
2. DESIBEL
3. AIRFLOW
4. FREQUENCY

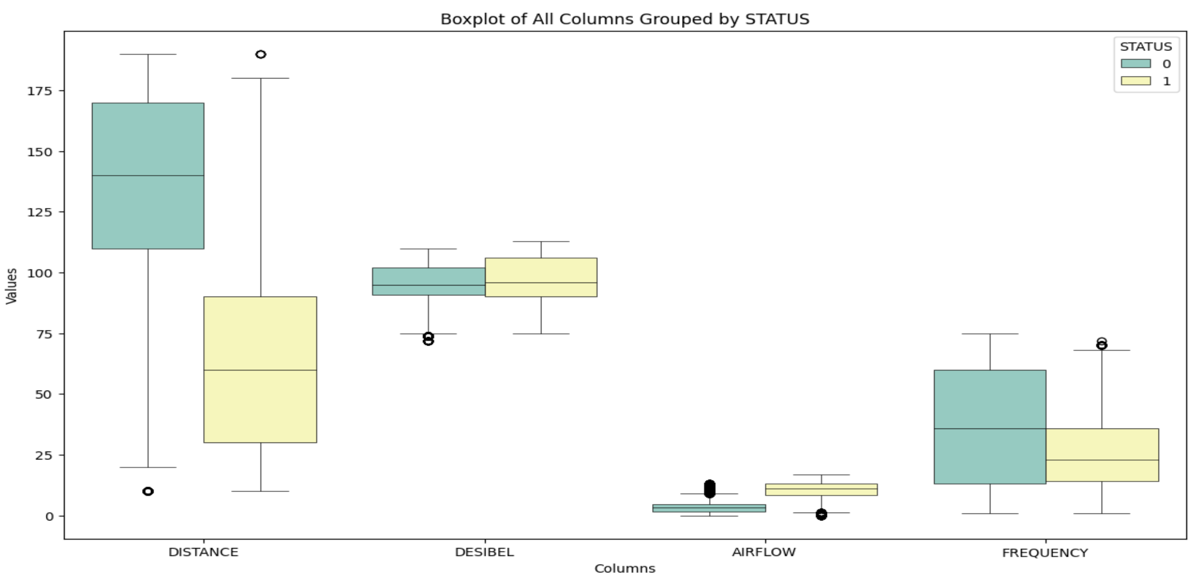


Figure 6: Boxplot of Numerical Features Grouped by ‘STATUS’ (Without ‘SIZE’)

No Outliers in 'SIZE': Confirmed that no outliers were found in the 'SIZE' column.

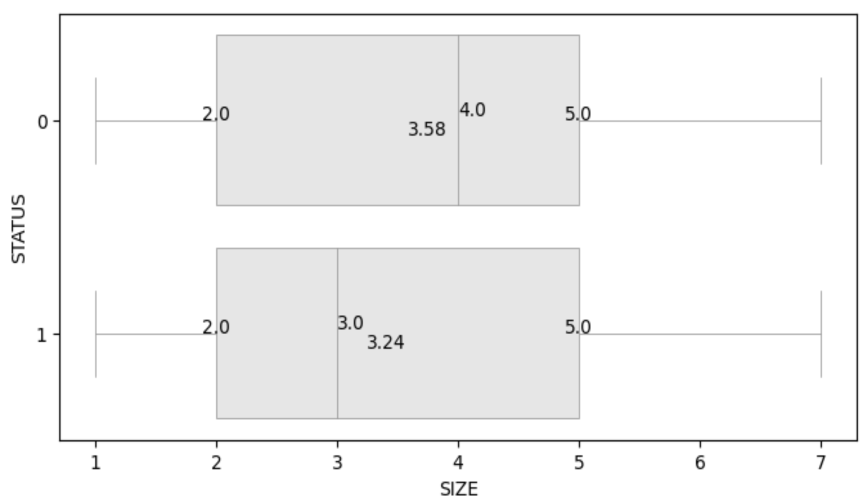


Figure 7: Boxplot of ‘SIZE’ Grouped by ‘STATUS’

Outlier Treatment using Winsorization:

- **Calculate IQR:** For each column with identified outliers, calculate the interquartile range (IQR) using the formula:
- IQR=Q3−Q1 where Q1 is the first quartile (25th percentile) and Q3 is the third quartile (75th percentile).
- **Determine Bounds:** Calculate the lower and upper bounds for outlier capping:
- **Lower Bound:** Lower Bound=Q1−1.5×IQR
- **Upper Bound:** Upper Bound=Q3+1.5×IQR
- **Cap Outliers:** Replace any values below the lower bound with the lower bound value and any values above the upper bound with the upper bound value.

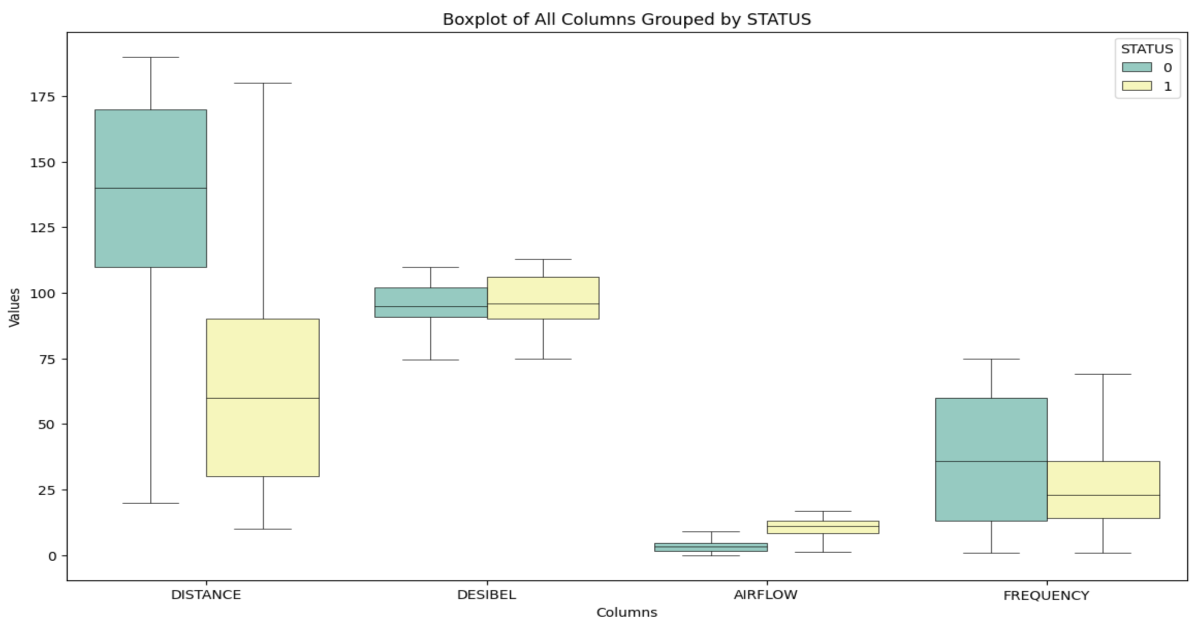


Figure 8: Boxplot of Numerical Features Grouped by ‘STATUS’ After Capping the Outliers

4.3 Model Fitting and Evaluation

In this study, several machine learning models were employed to classify the flame extinction status based on sound wave data. The performance of these models was assessed using various evaluation metrics such as Accuracy, Precision, Recall, F1 Score, Specificity, AUC (Area Under the Curve), Cohen's Kappa, and Matthews Correlation Coefficient (MCC). Below is a detailed description of the models' performance:

The K-Nearest Neighbors (k-NN) model achieved a high accuracy of 97.02%, demonstrating strong predictive power. Its precision, recall, and F1 score were all similarly high (97.02%, 97.13%, and 97.07% respectively), indicating that the model is effective in both identifying true positives and minimizing false positives. The AUC score of 0.9910 further confirms the model's ability to distinguish between flame extinguishing and non-extinguishing states. The Cohen's Kappa and MCC scores, both 0.9404, signify a strong agreement between predicted and actual labels, highlighting the model's overall robustness.

The Support Vector Machine (SVM) model performed similarly, with an accuracy of 96.99%. While its precision, recall, and F1 score were marginally lower than those of k-NN, they still reflect excellent performance (96.96%, 97.13%, and 97.04%, respectively). The model's AUC of 0.9968 is notably high, indicating strong classification performance. Cohen's Kappa and MCC values of 0.9398 point to a high level of agreement, suggesting reliable predictions across different instances.

The LightGBM model outperformed all other models, achieving the highest accuracy of 98.77%. Its precision (98.65%), recall (98.93%), and F1 score (98.79%) indicate its exceptional capability to correctly classify both positive and negative cases. The model's AUC score of 0.9991 underscores its near-perfect ability to differentiate between classes. Cohen's Kappa and MCC, both 0.9753, indicate excellent model stability and consistency in its predictions, making LightGBM a top performer in this classification task.

XGBoost also demonstrated strong performance with an accuracy of 98.48%, and similarly high precision (98.48%), recall (98.54%), and F1 score (98.51%). The model's AUC of 0.9988 suggests excellent separability between flame extinction and non-extinction cases. Cohen's Kappa (0.9696) and MCC (0.9696) reinforce XGBoost's consistent and reliable classification.

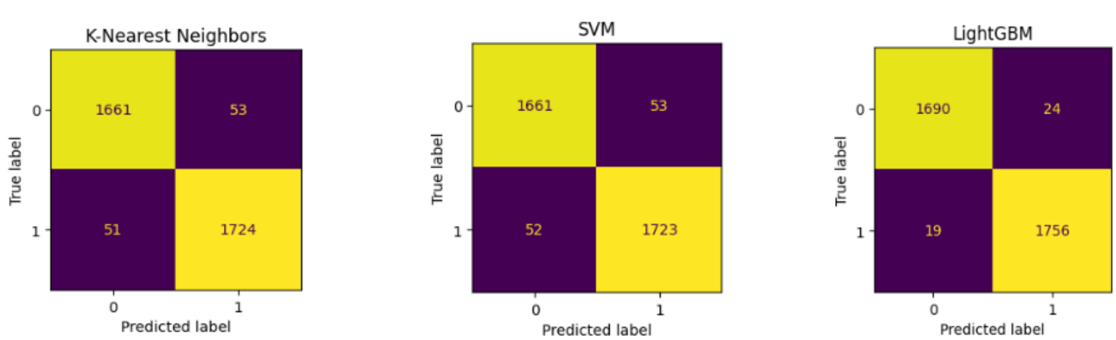
The Random Forest model achieved an accuracy of 98.22%, slightly trailing behind XGBoost and LightGBM. Its precision (98.53%), recall (97.97%), and F1 score (98.25%) remained strong, indicating a well-rounded classification model. The AUC score of 0.9981, along with Cohen's Kappa (0.9645) and MCC (0.9645), show that Random Forest is another reliable model in this study, although it slightly underperformed compared to LightGBM and XGBoost.

The Stacking model, which combines multiple models (LightGBM, XGBoost, and Random Forest), showed remarkable performance with an accuracy of 98.68%. Its precision (98.59%), recall (98.82%), and F1 score (98.71%) are close to LightGBM's values, reflecting its potential

to generalize well across varying datasets. With an AUC of 0.9919 and Cohen's Kappa (0.9736) and MCC (0.9736), the stacking model demonstrates that the combination of base learners enhances predictive performance, making it one of the best-performing models in this task.
Finally, the Artificial Neural Network (ANN) performed solidly, with an accuracy of 96.96%. Although slightly behind some of the other models, its precision (97.49%), recall (97.58%), and F1 score (97.03%) indicate strong performance. The AUC score of 0.9965 further supports its good classification capabilities, while Cohen's Kappa (0.9392) and MCC (0.9393) show that the ANN model is reliable, though not as high-performing as models like LightGBM and Stacking.
Overall, while all models demonstrated strong classification capabilities, LightGBM and Stacking stood out as the top performers. Their higher accuracy, precision, recall, and AUC scores suggest that these models are highly suitable for the task of classifying flame extinction, possibly offering better generalization than traditional models like k-NN and SVM. Additionally, the consistent performance of the Stacking model highlights the potential of model ensemble techniques to boost prediction accuracy.

Model	Accuracy	Precision	Recall	F1 Score	Specificity	AUC	Cohen Kappa	MCC
K-Nearest Neighbors	0.9702	0.9702	0.9713	0.9707	0.9691	0.9910	0.9404	0.9404
SVM	0.9699	0.9696	0.9713	0.9704	0.9685	0.9968	0.9398	0.9398
LightGBM	0.9877	0.9865	0.9893	0.9879	0.9860	0.9991	0.9753	0.9753
XGBoost	0.9848	0.9848	0.9854	0.9851	0.9842	0.9988	0.9696	0.9696
Random Forest	0.9822	0.9853	0.9797	0.9825	0.9848	0.9981	0.9645	0.9645
Stacking	0.9868	0.9859	0.9882	0.9871	0.9854	0.9919	0.9736	0.9736
ANN	0.9696	0.9649	0.9758	0.9703	0.9632	0.9965	0.9392	0.9393

Table 4: Performances of the models



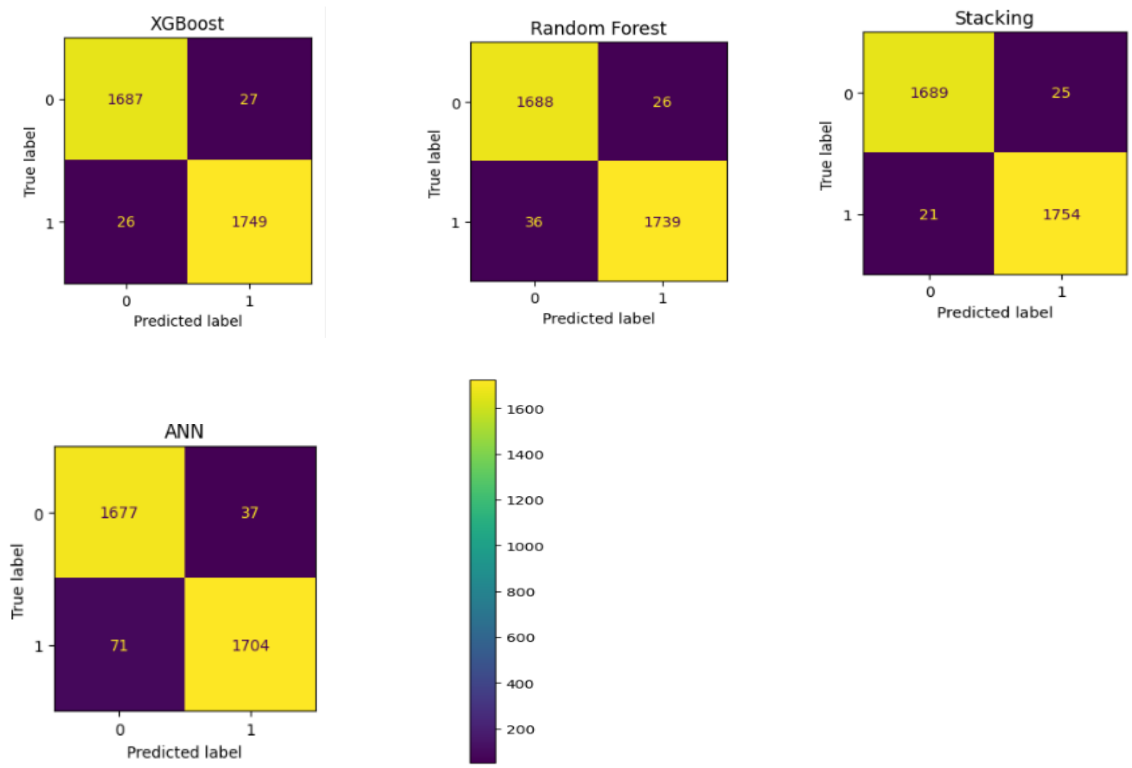


Figure 9: Confusion Matrices

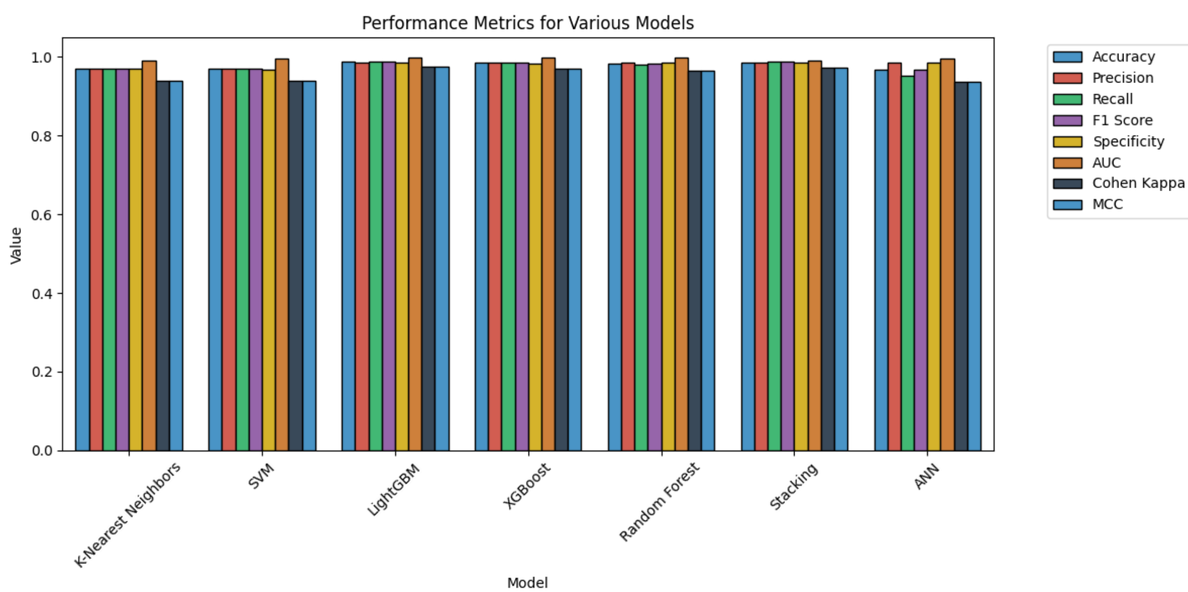


Figure 10: Barplot of Evaluation Metrics

4.4 CN2 Rule Learning Result

The CN2 Rule Induction model demonstrated strong performance in classifying the data, as reflected in both the confusion matrix and key performance metrics. The confusion matrix shows that the model correctly classified 6,776 true negatives and 6,823 true positives, while it misclassified 196 false positives and 159 false negatives out of a total of 13,954 samples. The model's classification accuracy (CA) is 97.5%, indicating that the model made correct predictions in 97.5% of the cases. The F1 score of 0.975 shows a good balance between precision and recall, with the precision and recall values both standing at 0.975, meaning that 97.5% of the predicted positives were accurate, and 97.5% of the actual positives were correctly identified. Additionally, the AUC (Area Under the Curve) is 0.996, demonstrating the model's excellent ability to distinguish between classes. The Matthews Correlation Coefficient (MCC) of 0.949 reflects a strong agreement between true and predicted values, confirming the robustness and generalization capability of the model.

Model	AUC	CA	F1	Prec	Recall	MCC
CN2 Rule Induction	0.996	0.975	0.975	0.975	0.975	0.949

Actual \ Predicted	0	1	Σ
0	6776	196	6972
1	159	6823	6982
Σ	6935	7019	13954

Figure 11: Evaluation Metrics and Confusion Matrix of CN2 Rule Learning Algorithm

The Hyper parameters were:

- Evaluation Measure: Laplace Accuracy
- Beam Width: 5
- Minimum Rule Coverage: 3
- Maximum Rule coverage: 5

4.5 Cross Validation Results

The predictive performance of various models employed in the fire extinction project was rigorously assessed through a five-fold cross-validation process. This method provided a robust estimate of the models' generalization capabilities, particularly in predicting the extinction status of flames under varying conditions.

LightGBM Results

The LightGBM model demonstrated commendable performance, with the cross-validation scores being 0.8977, 0.8366, 0.8736, 0.9323, and 0.9103. The mean score for the LightGBM model was calculated to be 0.8901, accompanied by a standard deviation of 0.0328. This indicates a generally high predictive accuracy, with a reasonable level of stability across the different folds.

Random Forest Results

The Random Forest model exhibited even stronger performance, with cross-validation scores of 0.9200, 0.8604, 0.8994, 0.9045, and 0.9126. The mean score for the Random Forest model was 0.8994, with a standard deviation of 0.0207. This suggests that the Random Forest model not only achieved a higher average accuracy compared to LightGBM but also exhibited a lower variability in performance, highlighting its robustness in flame extinction prediction.

Stacking Results

The Stacking model's cross-validation scores were 0.9091, 0.8507, 0.9045, 0.8842, and 0.9137. The mean score for the Stacking model was found to be 0.8924, with a standard deviation of 0.0232. Although the Stacking model's average performance was slightly lower than that of the Random Forest model, it still demonstrated a solid predictive capability with minimal variability.

Comparative Analysis

In summary, the cross-validation results revealed that all three models achieved strong predictive accuracies, with Random Forest leading the performance metrics. The mean scores indicate that while LightGBM and Stacking also performed well, Random Forest's lower standard deviation suggests greater reliability in its predictions. These findings underscore the effectiveness of advanced machine learning techniques in enhancing the accuracy and robustness of fire extinction prediction systems, paving the way for more reliable decision-making in fire suppression applications.

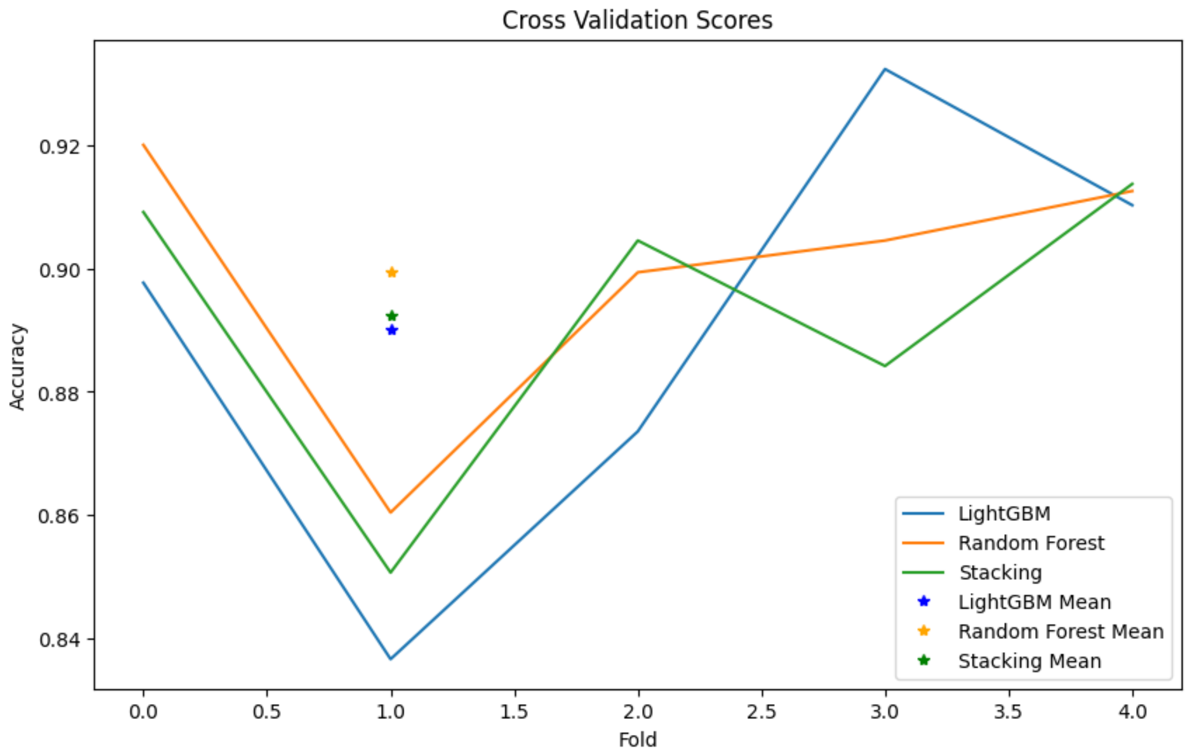


Figure 12: Cross Validation Results

4.6 SHAP Results

The SHAP summary plot (Figure 13) visualizes the importance of each feature in determining the model's predictions, offering valuable insights into the role and impact of individual features. The features are ranked in descending order of importance, with DISTANCE being the most influential, followed by AIRFLOW, FREQUENCY, and others. This ranking is crucial as it highlights which variables are most significant in the model's classification of flame extinction versus non-extinction.

The x-axis represents the SHAP values, indicating how much each feature contributes to either increasing or decreasing the model's output. A positive SHAP value indicates that the feature pushes the prediction towards a higher probability of flame extinction, whereas a negative SHAP value suggests a lower probability. For instance, DISTANCE displays a wide range of SHAP values, signifying its strong influence in either raising or lowering the predicted probability. Higher DISTANCE values (depicted in red) generally increase the model's prediction, indicating that greater distances correlate with a higher likelihood of flame extinction. Conversely, lower values of DISTANCE (depicted in blue) reduce the predicted probability of flame extinction.

The color gradient in the plot reflects the actual feature values for each instance, where red represents higher feature values and blue indicates lower values. This gradient allows for the interpretation of how specific feature values influence the model's predictions. For example, high AIRFLOW values (red) typically result in negative SHAP values, meaning they lower the predicted probability of flame extinction, suggesting that high airflow may hinder flame suppression. On the other hand, SIZE exhibits a pattern where larger values contribute positively to the prediction, suggesting that greater sizes of flames correspond with a higher likelihood of being extinguished.

Each feature's SHAP values are distributed across a wide range, showing the variability in its impact on the model's output. DISTANCE exhibits the largest spread of SHAP values, further reinforcing its significance in the classification task. In contrast, other features, such as DESIBEL and FUEL_lpg, have smaller distributions of SHAP values, indicating a lesser but still notable effect on the model's decisions.

This SHAP analysis provides an intuitive and transparent interpretation of feature importance, allowing for a deeper understanding of the model's inner workings. The insights gained here confirm that variables such as DISTANCE, AIRFLOW, and FREQUENCY are not only statistically significant but also practically important in predicting flame extinction, making them key factors in the development of a robust fire suppression system. By quantifying the contribution of each feature, SHAP values ensure that the model's predictions are interpretable, enhancing the model's reliability for real-world applications in fire safety.

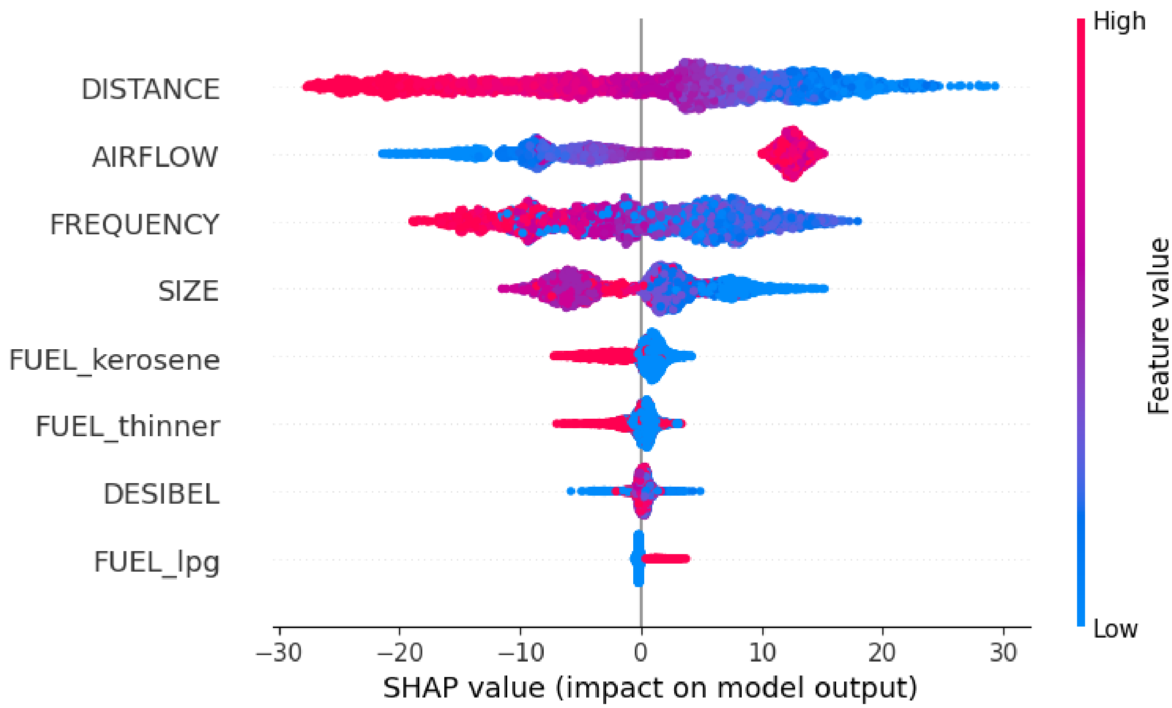


Figure 13: SHAP values of Feature Impotances

CHAPTER 5
DISCUSSIONS AND CONCLUSION

5.1 Discussion

The focus of this project was to explore the potential of sound wave technology in fire suppression, a relatively novel approach that aims to extinguish flames by manipulating sound frequencies, airflow, and sound pressure. Through a series of experiments, we gathered detailed data on the interaction between these variables, including frequency, decibel levels, and airflow, and their effects on the extinguishing process. Machine learning techniques were employed to model and predict the extinguishing and non-extinguishing states of the flame, helping to enhance our understanding of the key factors influencing the efficiency of the system.

One of the critical steps in the project was performing a correlation analysis to investigate the relationships between the features in the dataset. The results revealed significant connections between the core variables involved in the extinguishing process. Notably, an increase in frequency was associated with higher decibel levels, while airflow decreased as frequency rose, demonstrating an inverse relationship. Additionally, distance was shown to negatively affect airflow, highlighting its critical role in optimizing flame suppression efficiency. The frequency of the sound wave emerged as the most influential factor, confirming its importance in determining the effectiveness of the extinguishing process. These correlations provided valuable insights into how sound waves influence the flame extinguishing mechanism and how various parameters must be fine-tuned to achieve optimal results.

The application of machine learning models was a pivotal aspect of this project. We trained multiple models—K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), XGBoost, LightGBM, Artificial Neural Networks (ANN), and a Stacking model—using experimental data. Cross-validation was employed to ensure the reliability of the models' predictions and to objectively assess their classification accuracy in determining the flame's extinguishing or non-extinguishing states.

Among the models, Stacking, which integrated XGBoost, LightGBM, and Random Forest as base models, emerged as the best performer with an accuracy of 98.68%, precision of 98.59%, and a recall of 98.82%. LightGBM followed closely with a similarly high accuracy of 98.77%, while XGBoost and Random Forest also exhibited strong classification performance. These models were able to correctly classify the majority of data samples, as shown by their high F1 scores, AUC values, and Cohen Kappa statistics. The confusion matrices generated for each model provided a clear understanding of how accurately the models predicted flame extinction. The relatively small differences in accuracy between the models, while seemingly minor, translated into significant differences in the number of correctly classified data points given the large size of the dataset.

Interestingly, despite the ANN model being widely used in many predictive tasks, it slightly underperformed compared to the tree-based models and Stacking. This could be due to the non-linear relationships in the data, which are better captured by ensemble methods like Random Forest, LightGBM, and XGBoost. Overall, the machine learning approach offered a sophisticated decision-making framework for predicting flame extinguishing success, with Stacking and LightGBM leading the way in accuracy and robustness.

In this project, significant improvements were made over the previous work by Koklu and Taspinar (2011) by expanding the scope of machine learning techniques and enhancing outlier management strategies. While their study demonstrated strong classification accuracies with a limited selection of models, this research employed a broader array of advanced algorithms, including LightGBM, XGBoost, and Stacking models, which contributed to improved predictive performance in fire suppression systems. Additionally, the integration of the Winsorization method for outlier management mitigated the impact of extreme values, leading to more reliable and accurate predictions. By employing SHAP for feature importance, this project not only provided insights into the key factors influencing flame extinguishing success but also enhanced the interpretability of the machine learning models. Overall, these advancements underscore the potential for optimizing fire suppression strategies using sound wave technology, setting a foundation for future research in this area.

5.2 Practical Implications

The results from this project have significant implications for fire suppression systems using sound waves. We determined that specific frequency ranges were most effective in extinguishing flames, depending on the distance from the fire source. For instance, frequencies between 10–50 Hz were optimal for distances of 10–100 cm, while lower frequencies (10–28 Hz) were more effective at greater distances (100–180 cm). In the case of liquid petroleum gas

(LPG) fuel, the ideal frequency range for flame suppression was found to be between 10–45 Hz for distances of 10–140 cm. These findings are crucial for optimizing the use of sound wave technology in practical applications.

Furthermore, the sound intensity generated during the experiments (ranging from 85 to 113 dB depending on the distance) and the airflow produced by sound pressure were critical factors. The airflow created by sound pressure reached 17 m/s at a frequency of 30 Hz at a distance of 10 cm, significantly enhancing the cooling effect on the fuel container. This rapid cooling, almost twice as fast as under normal conditions, emphasizes the effectiveness of sound waves not only in extinguishing flames but also in managing heat and preventing re-ignition.

5.3 Conclusion

This project successfully explored the application of sound wave technology in fire suppression, revealing its potential as an effective alternative to traditional methods. Through detailed correlation analysis, we identified critical relationships between sound frequencies, airflow, and decibel levels that influence flame extinguishing processes. The use of advanced machine learning techniques, including LightGBM, XGBoost, Random Forest, and Stacking models, significantly enhanced predictive capabilities, while the Winsorization method improved outlier management. Additionally, SHAP was employed for feature importance analysis, offering insights into the key factors affecting model performance. The findings have practical implications for optimizing sound wave fire suppression systems, establishing a foundation for future research in this innovative area and contributing to improved fire safety measures.

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