A Comparative Analysis of Machine Learning Approaches for Sound Wave Flame Extinction System Towards Environmental Friendly Fire Suppression

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Abstract— **The devastation caused by fires is a significant threat to human life. There are traditional fire extinguishing methods but can have negative impacts on the environment. This study utilized data from a system that uses sound waves to extinguish fires without requiring water and chemicals. This paper created machine learning models that can predict whether a fire can be extinguished by the sound waves given the features like the size, fuel, distance, decibel, airflow, and frequency. The researchers used Python programming to create different machine learning models and determined the most accurate model using the classification accuracy and F1 score as performance metrics. The XGBoost model was identified as the most effective in classifying the sound wave flame extinction with accuracy scores of 98.31% and 98.62% for the model with default and optimized parameters, respectively.**

Keywords—fire suppression, machine learning, acoustic waves

I. INTRODUCTION

Fire remains an essential resource that serves various purposes for modern living. Despite its many benefits, fire can also be a destructive force that poses significant risks to both living and non-living things if not handled carefully and appropriately. [1] Thus, detecting and extinguishing fires promptly is of paramount importance due to the potential damage associated with uncontrolled fires. Fires can be put out using a variety of extinguishing agents, such as water, halon, carbon dioxide, common dry chemicals, and other gases. [2] Continually exploring and discovering other conventional ways can be an integral part in developing a fire extinction system. According to the Bureau of Fire Protection (BFP), the number of fire incidents increased by almost 13% in the first two months of 2022 compared to the same period in 2021. From January to March 1, there were 2,103 fire incidents, which is a 12.88% increase from the 1,863 incidents that occurred during the same period in the previous year. [3]

The increased frequency and severity of wildfires, such as those in California and Australia, pose new dangers to both the environment and its inhabitants. In California, the annual area destroyed by wildfires has increased five-fold between 1972 and 2018. [4]

Advanced technology offers a potential solution to the increasing damage caused by wildfires using an acoustic fire extinguisher that employs sound waves to displace oxygen and disrupt the combustion triangle, which is necessary for fire ignition and sustenance. The device uses low-frequency bass (30 to 60Hz) to extinguish flames without requiring water or chemicals. [5] Results have shown that sound waves can more easily put out fires in low-gravity environments than in normal gravity. [6] The use of the acoustic technique is considered a new and innovative way to put out fires, offering numerous advantages, including zero pollution, no need to replenish extinguishing agents, and a cost-effective and eco-friendly solution since it does not rely on chemical products. [7]

A machine-generated system has demonstrated potential in creating a fire extinguishing system that utilizes sound waves. Based on its performance, the system has exhibited its capability to minimize the chances of fires transpiring, and it can be employed on numerous occasions. This study aims to explore various options and select the most effective model for extinguishing fires with the use of sound waves. Decision Tree, Extra Trees Classifier, Gaussian Naïve Bayes, K-Nearest Neighbor, Logistic Regression, Random Forest, Linear Discriminant Analysis, and eXtreme Gradient Boosting were some of the common models used in this study to accurately classify and select data using Python.

II. REVIEW OF RELATED WORKS

A fire extinguisher is a piece of equipment designed primarily for fighting fires. It is typically utilized by fire departments and is most effective when used in the early stages of a fire's development. The primary advantages of a fire extinguisher are its simplicity of use, ease of handling, lack of residual effects after use, and doesn't harm the environment. [9]

Extensive research and innovation are crucial to do in the field of manual fire extinguishing techniques and apparatus for the fire department. Most of the conventional methods of fire extinguishing are water [8][9], foam [8][10], carbon dioxide, and dry chemicals [15][16][21][22][24][25]. The kind of extinguishing agent used will depend on the type of fire. The use of the incorrect type of extinguisher may worsen the fire and lead to more damage [16]. In most circumstances, water is a practical and accessible fire suppression agent. Studies have revealed that just a modest amount of water is required to put out fires in residential structures [9]. As a result, using less water to put out fires helps the environment, prevents water damage, and eases the strain on the water supply system [8][21]. It's important to realize that not all fires can be put out with water, and that other fire suppression methods can be more suited in some circumstances. Foam is used to put out fires brought on by petroleum products. Chemical analysis research on AFFF (Aqueous Film Forming Foam) has demonstrated that optimizing the ratio of gas to liquid can enhance foam expansion and drainage. The capacity to cool and cover a fire is improved as a result, providing the best fire-extinguishing performance [13]. The main aspect affecting how effectively foam extinguishes fires is how active its surface is when it meets oil [10]. Also, during fire suppression operations, it is frequently dangerous for pool fires to re-ignite. Yet, the application of dry compounds with oleophobic qualities can be a solution to this issue. Such powders can successfully float on top of the fuel pool's oil and inhibit fuel from evaporating, which ultimately prevents the fire from re-igniting [15]. While numerous situations have shown these techniques to be effective, they can also have detrimental effects on the environment, such as water contamination, thus it is necessary to develop more eco-friendly and sustainable alternatives. To advance fire safety technology and investigate novel fire suppression techniques that can better address changing fire hazards and difficulties, continuous research and development is essential.

As new materials and technologies are created, special fire dangers arise. To address this, Kim et. al [11] investigated the effectiveness of using Sound Fire Extinguishers in enclosed spaces such as ducts that connect elevators, communication lines, and electrical lines. Sound Fire Extinguishers utilize sound waves instead of conventional fire suppression agents like water or chemicals, making them suitable for use in any environment that may be economically impacted by fire damage [23][24]. According to this study, Sound Fire Extinguishers are an efficient and sustainable fire suppression option for confined areas [12][23]. According to Tiwary et al. [12], a portable sound wave extinguisher has various benefits, including being inexpensive, chemical-free, and usable in limited spaces. Finding the most efficient frequency at which sound waves may be created to put out fires is the main problem in designing a sound wave extinguisher. Since it is the most important factor in producing a good extinguisher, this factor is crucial and should be given the utmost consideration when developing any sound wave extinguishing equipment [12][14]. According to Zaid et al. [14], the subwoofer's production of acoustic waves with a low frequency can put out fires. Fire can be extinguished between 40Hz to 60Hz and the sound wave can extinguish the fire of all types of flames. The fire suppression needs to be done at the incipient stage where the heat and flame produced by the fire is at the minimum point [20][26].

As stated by Stawczyk, P. & Wilk-Jakubowski, J. [26], acoustic waves with lower frequencies are better for extinguishing fires because they create stronger vibrations in the flames, leading to better extinguishing results. The experiments revealed that the frequency with the best extinguishing performance was 14 Hz, and it required less electrical power to operate the extinguisher. Hence, it makes sense to design acoustic fire extinguishing devices that operate at the lowest frequencies possible. [26].

The study of Bae et al. [11] involved testing the effectiveness of fire extinguishers in a duct environment that included obstacles like elevators and electric wires. It was found that even in complex structures, the fire extinguisher was able to effectively extinguish the fire. Furthermore, when the sound fire extinguisher was activated, the long lighter did not ignite, indicating its ability to effectively extinguish fires in challenging environments with obstacles [11][22].

In accordance with Gnatowska et al. [27], extinguishing flames becomes more challenging if there is an object near the fire source, even if it is directly behind it. This is because the sound pressure in that area intensifies, but the presence of the object makes it harder to extinguish the flames. Additionally, the nearer the object is to the flames, the more acoustic pressure is needed to trigger an extinction event.

Koklu and Taspinar [17] utilized a dataset to test five distinct machine learning approaches: artificial neural network, k-nearest neighbor, random forest, stacking, and deep neural network. Stacking is an ensemble method that combines artificial neural network, k-nearest neighbor, and random forest models. The models were used to classify whether a flame was in an extinction or non-extinction state, and the accuracy of the models was thoroughly evaluated through the 10-fold cross-validation method to assess their potential for use as a decision support system for the sound wave fire-extinguishing system. The performance of each method was compared through analysis of their respective performance metrics. Results showed that the stacking model had the highest classification accuracy at 97.06%, followed by random forest at 96.58%, artificial neural network at 96.03%, deep neural network at 94.88%, and k-NN at 92.62%. The decision support system derived from these findings could help enhance the efficiency of the acoustic wave fire-extinguishing system. Since the effectiveness of sound wave-based flame extinction declines as dripping velocity rises, the sound wave is more effective to put out dripping flames in the early stages. [17][19][20]

Abrar et al. [18] claimed that a sound-based fire extinguisher is a potentially revolutionary idea that is effective and efficient enough to be used in contemporary times [18][12]. It may, for instance, be installed in each electrical control panel and set up to activate anytime it detects a fire, with the frequency of the activation varying according to the intensity of the flames. For the width of the flames to be effective, the frequency must be suitable. Sound-based fire suppression has a wide range of potential uses, such as preserving astronaut lives or defending crucial control centers. It may also be used to extinguish fires in regions that are inaccessible to humans without risking their safety. Overall, employing sound waves to put out fires shows great promise and has the potential to revolutionize.

Based on the gathered research, it is evident that fire extinguishers are an essential tool for combatting fires and necessitate extensive research and development to enhance manual fire extinguishing techniques and equipment. The selection of fire suppression methods, such as water, foam, carbon dioxide, and dry chemicals, is contingent upon the nature of the fire. However, water is not effective in extinguishing all types of fires, and alternative approaches like foam and dry compounds may be more suitable in specific situations. To prevent environmental harm, it is crucial to develop sustainable and eco-friendly options. The use of sound waves, rather than traditional fire suppression agents, is an effective and sustainable alternative for enclosed spaces. For acoustic fire extinguishing devices, utilizing the lowest frequency possible produces more potent vibrations in the flames, leading to better extinguishing outcomes. Sound fire extinguishers have demonstrated their ability to extinguish fires effectively in challenging environments with obstacles.

Additionally, machine learning models have been explored to improve the sound fire extinguishing system. This research is crucial for utilizing the decision support system established through the findings of Koklu and Taspinar [17] and to decrease the number of features required while increasing classification accuracy. The high amount of data in the data set would also be effective in the decision-making process for the decision support system.

III. METHODOLOGY

A. Dataset Description

The study entitled "*Determining the Extinguishing Status of Fuel Flames with Sound Wave by Machine Learning Methods*" conducted by Yavuz Selim Taspinar and Murat Koklu [17] used a sound wave fire-extinguishing system with 4 subwoofers, 2 amplifiers, a control unit, and various instruments to measure temperature, airflow, sound intensity, and extinction time of 4 fuel flames.

Results acquired involved creating flames of varying sizes using three liquid fuels and LPG fuels, using different sized fuel cans and gas adjustments. During each experiment, the fuel container, anemometer, and decibel meter were moved incrementally from 10 cm to 190 cm while conducting fire extinguishing tests with 54 different sound wave frequencies at each distance and flame size. Out of the 17,442 tests conducted, 8,759 resulted in non-extinguishing flames, while 8,683 resulted in extinguishing flames.

The data collected in this study were used by the researchers to develop multiple machine learning models that can accurately predict the occurrence of fires. Among these models, the most effective one was chosen for implementation.

B. Proposed Work

Shown in Fig. 1 is the overview of the proposed work with the following stages: data wrangling, exploratory data analysis, feature selection, machine learning modelling, and evaluation.

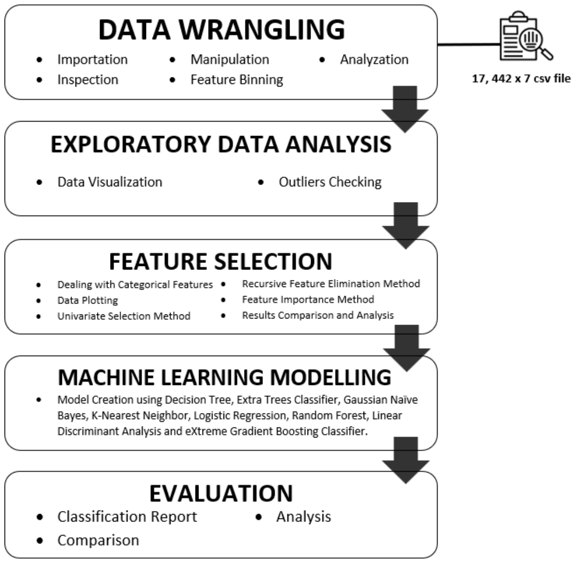

Fig. 1. Overview of Proposed Work

The first step that researchers take is to clean the raw data using data wrangling followed by exploratory data analysis and feature selection, to improve accuracy and avoid overfitting. They then develop models using various algorithms like Decision Tree, Extra Trees Classifier, Gaussian Naïve Bayes, K-Nearest Neighbor, Logistic Regression, Random Forest, Linear Discriminant Analysis and eXtreme Gradient Boosting Classifier. Models are created using default parameters, and an optimization process is carried out to enhance their accuracy and effectiveness. The best model is selected based on classification accuracy and F1-score metrics. The F1-scores of different models are compared to select the best model based on classification accuracy. Tabulating the F1-scores allows for a comparative analysis of the alternatives and identification of the most effective approach for extinguishing fires.

C. Development of the Intelligent Models

The researchers used various Machine Learning Models such as Decision Tree, Extra Trees Classifier, Gaussian Naïve Bayes, K-Nearest Neighbor, Logistic Regression, Random Forest, Linear Discriminant Analysis, and eXtreme Gradient Boosting Classifier. Decision Tree is one of the common Machine Learning models, it is a learning algorithm for classification and regression that uses a tree structure with a root, branches, internal nodes, and leaves. Extra Trees Classifier is also an ensemble learning technique that combines the results of multiple decision trees to classify data. Another one is the Gaussian Naïve Bayes, which is a simple and efficient probabilistic algorithm used for classification tasks. It assumes that features are independent and normally distributed, calculates probabilities using Bayes' theorem, and selects the class with the highest probability as the prediction. Moreover, K-Nearest Neighbor (KNN) is a non-parametric algorithm for classification and regression that predicts a label or value based on the majority vote or average of the K closest neighbors to a data point. It's used with distance metrics and works well with both numerical and categorical data.

Logistic Regression is a classification algorithm that models event probability using a logistic function. It can handle binary and multiclass problems, regularized to prevent overfitting, with easily interpretable coefficients indicating feature importance. It can predict class probability, regardless of response variable type. Additionally, Random Forest Classifier (R) is a classification algorithm that uses multiple decision trees, each trained on a different subset of data and using a random set of features. It makes predictions by combining the predictions of individual trees through voting or averaging. It can handle both numerical and categorical data as well. On the other hand, Linear Discriminant Analysis (LDA) is a linear algorithm that is used for classification and finds a lower-dimensional space projection that maximizes the separation between different classes while minimizing the variance within each class. Lastly, the researchers also used the eXtreme Gradient Boosting (XGB). It uses an optimized version of the gradient boosting decision tree method to improve accuracy and minimize errors in classification tasks.

This study used Python to predict the most effective model for extinguishing fire using sound waves. The dataset was split into a training set which is 80 % and testing set with is 20%. The former was used to build machine learning models, while the latter was used to validate them. The best model was chosen based on classification accuracy, and its performance in determining the best outcome was assessed using the F1-score.

IV. RESULTS AND DISCUSSION

A. *Dataset Generation for Machine Learning*

A dataset of 17,442, conducted by Yavuz Selim Taspinar and Murat Koklu [17], were used to predict the best Machine learning model that can extinguish flames using sound waves with the Python programming using Anaconda navigator. Table I presents the data information, including appropriate data types, without any missing values.

TABLE I. DATA INFORMATION

Range Index: 17442 entries, 0 to 17441			
#	Column	Non-Null Count	Data Type
0	SIZE	17442 non-null	int64
1	FUEL	17442 non-null	object
2	DISTANCE	17442 non-null	int64
3	DECIBEL	17442 non-null	int64
4	AIRFLOW	17442 non-null	float64
5	FREQUENCY	17442 non-null	int64
6	STATUS	17442 non-null	int64
Dtypes: float64 (1), int64 (5), object (1)			

To enhance the accuracy of machine learning models and prevent overfitting, the process of feature selection is employed on the data. Figures 2, 3, and 4 display the chosen features obtained through various selection methods for univariate selection, recursive feature elimination, and feature importance respectively.

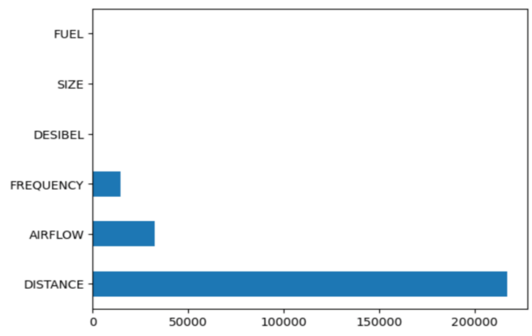

Fig. 2. Feature Selection Using Univariate Method

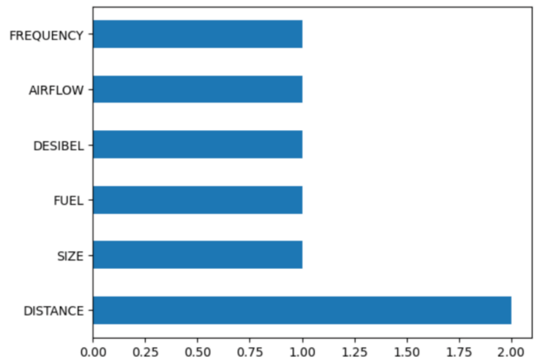

Fig. 3. Feature Selection Using Recursive Feature Elimination

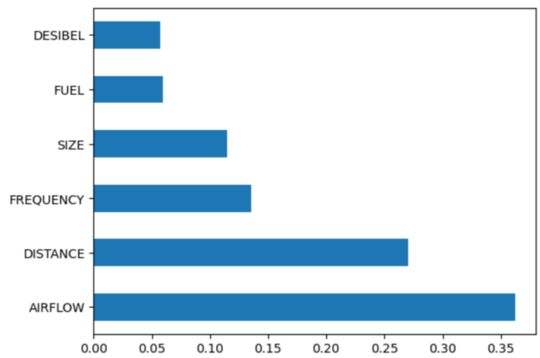

Fig. 4. Feature Selection Using Feature Importance Method

Out of the three techniques used for selecting features, the Feature Importance method has provided clear and understandable outcomes for the chosen features. Despite this, the features of Decibel and Fuel have resulted in similar levels of importance. Thus, the researchers decided to create distinct models utilizing either Decibel or Fuel, and the model that was created using Fuel produced better results. The final set of features considered for the model includes airflow, size, frequency, distance, and fuel.

B. *Performance of the Machine Learning Models*

To ascertain which classifier has the highest accuracy rate in detecting fires using sound waves, several Machine Learning algorithms, including Decision Tree, Extra Trees Classifier, Gaussian Naive Bayes, K-Nearest Neighbor, Logistic Regression, Random Forest, Linear Discriminant Analysis, and eXtreme Gradient Boosting, were used. During the model training, hold-out validation and 10-fold stratified cross-validation procedures were utilized to ensure accurate findings and prevent overfitting and high variation. The training process was further optimized by using RandomSearchCV with number of iterations equal to 100 to get the optimum parameter values. Table II shows the cross-validation results for models using all features, selected features, and with default parameters using accuracy as a scoring metrics. The XGBoost Classifier provided the best performance among all the models utilizing default parameters. However, the results for all models improved significantly using optimized parameters of the models as shown in Table IV.

TABLE II. CROSS-VALIDATION USING ACCURACY SCORE FOR MODELS WITH ALL FEATURES AND SELECTED FEATURES AND WITH DEFAULT PARAMETERS

Model	Accuracy Score	
	All Features	Selected Features
Logistic Regression	0.8759	0.8750
Gaussian NB	0.8736	0.8727
Linear Discriminant Analysis	0.8745	0.8745
K Neighbors Classifier	0.9215	0.9312
Decision Tree Classifier	0.9676	0.9722
Random Forest Classifier	0.9627	0.9711
Extra Trees Classifier	0.9665	0.9754
XGB Classifier	0.9825	0.9831

Table III shows the cross-validation results for models using selected features and with default parameters using precision, recall, and F1 score as a scoring metrics.

TABLE III. CROSS-VALIDATION USING PRECISION, RECALL, AND F1 SCORE FOR MODELS WITH SELECTED FEATURES AND WITH DEFAULT PARAMETERS

Model	Non-extinguishing			Extinguishing		
	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Logistic Regression	0.86	0.90	0.88	0.89	0.86	0.87
Gaussian NB	0.85	0.90	0.87	0.90	0.84	0.87
Linear Discriminant Analysis	0.84	0.91	0.88	0.91	0.84	0.87
K Neighbors Classifier	0.92	0.94	0.93	0.94	0.93	0.93
Decision Tree Classifier	0.97	0.97	0.97	0.97	0.97	0.97
Random Forest Classifier	0.97	0.97	0.97	0.97	0.97	0.97
Extra Trees Classifier	0.97	0.98	0.98	0.98	0.97	0.98
XGB Classifier	0.98	0.99	0.98	0.99	0.98	0.98

Table IV shows the cross-validation and hold-out validation results for models using selected features and with optimized parameters using accuracy as a scoring metrics.

TABLE IV. CROSS-VALIDATION AND HOLD-OUT VALIDATION USING ACCURACY SCORE FOR MODELS WITH SELECTED FEATURES AND WITH OPTIMIZED PARAMETERS

Model	Cross Validation Accuracy	Hold-out Validation Accuracy
Logistic Regression	0.8756	0.8750
Gaussian NB	0.8723	0.8725
Linear Discriminant Analysis	0.8736	0.8745
K Neighbors Classifier	0.9388	0.9390
Decision Tree Classifier	0.9720	0.9719
Random Forest Classifier	0.9769	0.9733
Extra Trees Classifier	0.9803	0.9782
XGB Classifier	0.9834	0.9862

Table V shows the cross-validation results for models using selected features and with optimized parameters using precision, recall, and F1 score as a scoring metrics.

TABLE V. CROSS-VALIDATION USING PRECISION, RECALL, AND F1 SCORE FOR MODELS WITH SELECTED FEATURES AND WITH OPTIMIZED PARAMETERS

Model	Non-extinguishing			Extinguishing		
	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Logistic Regression	0.86	0.90	0.88	0.89	0.86	0.87
Gaussian NB	0.85	0.91	0.87	0.90	0.84	0.87
Linear Discriminant Analysis	0.84	0.91	0.88	0.91	0.84	0.87
K Neighbors Classifier	0.93	0.94	0.94	0.94	0.94	0.94
Decision Tree Classifier	0.97	0.97	0.97	0.98	0.97	0.97
Random Forest Classifier	0.97	0.97	0.97	0.97	0.97	0.97
Extra Trees Classifier	0.98	0.98	0.98	0.98	0.98	0.98
XGB Classifier	0.98	0.99	0.98	0.99	0.98	0.99

Figures 5 and 6 depict a comparison of the models' accuracy using cross-validation and hold-out validation for models with default parameters and with optimized parameters respectively. It shows that for all machine learning models, the XGBoost Classifier had the highest accuracy.

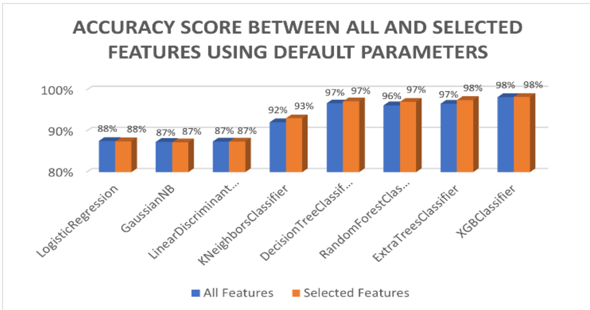

Fig. 5. Comparison of accuracy score between machine learning models in their default paarameters using all features versus selected features.

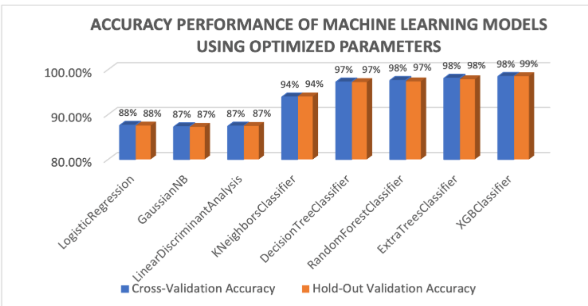

Fig. 6. Comparison of accuracy score between machine learning models in their default paarameters using all features versus selected features.

XGBoost Classifier has been identified as the best model since in predicting the status of the fire given the features as it showed an accuracy rate of 98.31% in default parameters and 98.62% in optimized parameters.

V. RESULTS AND DISCUSSION

In this study, 17,442 tests were evaluated using a variety of methods, such as the Decision Tree, Extra Trees Classifier, Gaussian Naive Bayes, K-Nearest Neighbor, Logistic Regression, Random Forest, Linear Discriminant Analysis, and eXtreme Gradient Boosting Classifier. To extract the essential results and obtain the best performance for each model, the researchers used a variety of techniques, including Data Wrangling, Exploratory Data Analysis, Feature Selection, Machine Learning Modelling, and Evaluation. Dataset features such as Size, Distance, Desibel, Airflow and Frequency are obtained. Using default and optimized parameters, the models' performance was evaluated during both the training and testing stages. The sound wave flame extinction system was classified most accurately by the XGBoost model, with accuracy ratings of 98.31% and 98.62% for testing default and optimized parameters, respectively. The proponents were able to reduce the number of features into five with a high accuracy rate. This indicates that sound wave fire extinguishing system can be used as a safe and effective way to intervene in a fire without causing harm to people or the environment.

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REFERENCES

[1] Mayuga, J. (2018). Tragedy of fires: Death and destruction in the Philippines. *Business Mirror.*

[2] O'Connor, B. (2021). Fire Extinguisher Types. *National Fire Protection Association.*

[3] Philippine star. (2022, march 2). Bfp: fires up by 13%. Retrieved from https://www.philstar.com/nation/2022/03/02/2164301/bfp-fires-13

[4] Taneja, S., & Bokade, P. (2019). Study and design of portable fire extinguisher. *Asia-Pacific Journal of Chemical Engineering*, 14(6), e2576. https://doi.org/10.1002/apj.2576

[5] Dell Technologies. (2021, March 10). Fighting fire with bass: Using sound waves to drown flames. Retrieved from https://www.dell.com/en-us/perspectives/fighting-fire-with-bass-using-sound-waves-to-drown-flames/#tab0=0

[6] Taneja, S., & Bokade, P. (2019). Study and design of portable fire extinguisher. *Asia-Pacific Journal of Chemical Engineering*, 14(6), e2576. https://doi.org/10.1002/apj.2576

[7] Wilk-Jakubowski, J.Ł. (2021). Analysis of Flame Suppression Capabilities Using Low-Frequency Acoustic Waves and Frequency Sweeping Techniques. *Symmetry 2021*, 13, 1299. https://doi.org/10.3390/sym13071299

[8] Aamodt, et al. (2021). Review of efficient manual fire extinguishing methods and equipment for the fire service. (https://www.researchgate.net/publication/350836504_Review_of_efficient_manual_fire_extinguishing_methods_and_equipment_for_the_fire_service)

[9] Binio & Kieliszek (2018). Analysis of the use for Fire Protection Water Supply Systems in public utility buildings and residential buildings. *MATEC Web of Conferences*. https://doi.org/10.1051/matecconf/201824700010

[10] Degaev, E. (2018). New classification of foaming agents for fire extinguishing. *MATEC Web of Conferences*. https://doi.org/10.1051/matecconf/201819302032

[11] Bae et al. (2021). A Study on a Suitability of Sound Fire Extinguisher in Duct Environment. *International Journal of Applied Engineering Research*. Volume 12, ISSN 0973-4562, Number 24, pp. 15796-15800.

[12] Tiwary et al. (2021). Portable Sound Wave Fire Extinguisher. *International Journal of Innovative Science and Research Technology*. Volume 6, Issue 5. ISSN No:-2456-2165

[13] Xu et al. (2018). Fire-extinguishing performance and mechanism of aqueous film-forming foam in diesel pool fire. *Elsevier*.

[14] Zaid et al. (2018). Fire Extinguisher Using Sound Waves. *Institutional Repository- AIKTC Library*.

[15] Zhao et. al (2018). Application of ultra-fine dry chemicals modified by POTS/OBS for suppressing aviation kerosene pool fire. *Fire Safety Journal*. Volume 118, 103148, ISSN 0379-7112, https://doi.org/10.1016/j.firesaf.2020.103148

[16] Cheng K. & Mei, J. (2021). A Study on Influencing Factors of Low Frequency Sound Wave Fire Extinguisher. *2020 8th International Conference on Power Electronics Systems and Applications (PESA). IEEE.* doi10.1109/PESA50370.2020.9343973

[17] Koklu, M., & Taspinar, Y. S. (2021). Determining the Extinguishing Status of Fuel Flames with Sound Wave by Machine Learning Methods. *IEEE Access.* doi:10.1109/ACCESS.2021.3088612

[18] Abrar et al. (2019). Fire Extinguisher using Sound Waves. *Anjuman-I-Islam's Kalsekar Technical Campus.*

[19] Huang et al. (2020). Extinguishing the dripping flame by acoustic wave. *Fire Safety Journal,* https://doi.org/10.1016/j.firesaf.2020.103109

[20] Choudhary et al. (2020). Designing of Fire Extinguisher Based on Sound Waves. *International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249 – 8958 (Online),* Volume-9 Issue-4, doi:10.35940/ijeat.D7301.049420

[21] Panchpor et al. (2019). Study of Acoustic Waves for Extinguishing Fires: A Review. *International Journal of Current Engineering and Technology. E-ISSN 2277 – 4106*, P-ISSN 2347 – 5161, Vol. 9, No. 1, doi: https://doi.org/10.14741/ijcet/v.9.1.10

[22] Shelke, Y. & Wable, P. (2019). Sound Wave Fire Extinguisher: Space and Duct Environment. *International Journal of Industrial Electronics and Electrical Engineering*, ISSN(p): 2347-6982, ISSN(e): 2349-204X Vol. 7, Issue 7, Jul. 2019

[23] Choudhary et al. (2020). A study on Sound Wave Fire Extinguisher with cooling rate. *International Journal of Advanced Engineering Research and Science (IJAERS)*, ISSN: 2349-6495(P), 2456-1908(O), Vol. 7, Issue 7, Jul. 2020, doi: https://dx.doi.org/10.22161/ijaers.77.57

[24] Bae, M. & Kim, B. (2019). A Study on High Power Amplifier of Sound Fire Extinguisher Using Pseudo Sinusoidal Wave. *International Journal of Engineering Research and Technology. ISSN 0974-3154,* Volume 12, Number 7 (2019), pp. 1133-1137, International Research Publication House.

[25] Yi, E.-Y. & Bae, M.-J. (2018). "On a fire extinguisher using sound winds", *Journal of Engineering and Applied Sciences,* Vol.13, No.4, 2018, pp. 977-980.

[26] Stawczyk, P. & Wilk-Jakubowski, J. (2021). Non-invasive attempts to extinguish flames with the use of high-power acoustic extinguisher. *De Gruyter*. doi: https://doi.org/10.1515/eng-2021-0037

[27] Gnatowska et al. (2018). Application of acoustic oscillations in flame extinction in a presence of obstacle. *XXIII Fluid Mechanics Conference (KKMP 2018), IOP Conf. Series Journal of Physics (Conf. Series 1101/2018).* doi: 10.1088/1742-6596/1101/1/012023.