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LabVIEW-based fire extinguisher model based on acoustic airflow vibrations

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ABSTRACT

In recent years, soundwave-based fire extinguishing systems have emerged as a promising avenue for fire safety measures. Despite this potential, the challenge is to determine the exact operating parameters for efficient performance. To address this gap, we present an artificial intelligence (AI)-enhanced decision support model that aims to improve the effectiveness of soundwave-based fire suppression systems. Our model uses advanced machine learning methods, including artificial neural networks, support vector machines (SVM) and logistic regression, to classify the extinguishing and non-extinguishing states of a flame. The classification is influenced by several input parameters, including the type of fuel, the size of the flame, the decibel level, the frequency, the airflow, and the distance to the flame. Our AI model was developed and implemented in LabVIEW for practical use.

The performance of these machine learning models was thoroughly evaluated using key performance metrics: Accuracy, Precision, Recognition and F1 Score. The results show a superior classification accuracy of 90.893% for the artificial neural network model, closely followed by the logistic regression and SVM models with 86.836% and 86.728% accuracy, respectively. With this study, we highlight the potential of AI in optimizing acoustic fire suppression systems and offer valuable insights for future development and implementation. These insights could lead to a more efficient and effective use of acoustic fire extinguishing systems, potentially revolutionizing the practice of fire safety management.

1. Introduction

Fire-related disasters, both natural and human-induced, pose significant threats to life, property, and the environment. Thus, the development of effective preventive measures is crucial in mitigating these risks [1] [2]. Conventional firefighting methods, which often entail the use of chemicals or heavy equipment, might inadvertently inflict further harm on infrastructure, natural resources, or the residents of the affected area [3], [4]. Hence, understanding the specific characteristics of the fire and the burning materials is of paramount importance for identifying the most suitable extinguishing technique [5]–[7].

In this context, the potential of sound waves as a means of fire suppression has garnered significant attention. This unique method could not only ensure the safety of people and the environment, but also present a cost-effective, environmentally friendly option [8], [9]. Sound wave-based fire extinguishing systems generate pressure waves that disrupt the combustion process and extinguish the fire, offering a safe, non-toxic, and non-caustic solution [10]. However, this technology is still in the research and development phase, necessitating further studies to optimize its effectiveness and efficiency.

Prior research indicates that both low-frequency sound waves (30 Hz to 50 Hz) and high-frequency

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sound waves (60 Hz to 90 Hz) can effectively disrupt combustion [11]–[17]. The efficacy of these acoustic waves depends on several factors including wave amplitude and source distance, both of which significantly influence flame dynamics. Moreover, other variables such as sound frequency, atmospheric conditions, and flame properties also play crucial roles [18], [19].

Considering the complexity of fire dynamics, there is a need for effective fire detection and suppression systems that can balance sensitivity, reliability, extinguishing efficiency, safety, and cost-effectiveness [20]–[23]. In this vein, the application of machine learning techniques and statistical analysis to study the characteristics of sound waves produced by flames offers promising advancements [24]. Coupled with the use of various sensors, cameras, and thermal imagers, data-driven approaches can provide a comprehensive understanding of fire behavior [25]–[30]. Such understanding can, in turn, contribute to the improvement of acoustic fire extinguishing systems [31]–[33].

In this study, we utilize a dataset comprised of 17,442 samples from experimental studies [34]–[37]. Our approach distinguishes itself from previous works through its innovative user interface and dynamic system. We propose a new model using LabVIEW, employing machine learning algorithms such as artificial neural networks, support vector machines, and logistic regression to predict flame extinguishing outcomes based on variables like fuel type, flame size, decibel level, frequency, airflow, and distance. The aim is to provide an decision-support system for sound wave fire extinguishing [34]–[37].

The paper is organized as follows: Section 2 elucidates the dataset, classification algorithms, and performance metrics used in our study. Section 3 presents the experimental results. Finally, Section 4 provides the conclusions drawn from this study.

2. Material and methods

In this section, we explain our systematic methodology, which covers the stages of data collection up to the culmination of the analysis. The process of data collection, the technical specifications of the collected dataset, and its dissemination are described in detail.

For the task of distinguishing between the extinguishing and non-extinguishing states of a flame, we used classification methods including artificial neural networks, support vector machines (SVM), and logistic regression. The rationale for these selected techniques and their relevance to our study are presented.

The efficiency of the classifiers was evaluated by applying performance metrics, namely accuracy, precision, recall, and F1-score. These metrics are briefly explained to allow an unbiased comparison of the performance of the classifiers used.

2.1. Data Acquisition

This research study utilized a dataset, derived from references [34]–[37], encompassing data aggregated from tests conducted on a fire extinguisher using four distinct fuel flames. The system framework is comprised of four subwoofers, two amplifiers, a control unit, and a computer employed as frequency sources. Ancillary instruments such as an anemometer, a decibel meter, a camera, and an infrared thermometer were engaged in measuring various parameters throughout the extinguishing process.

An expansive total of 17,442 experimental trials were executed utilizing this specified experimental apparatus. These trials were conducted within a fire chamber, explicitly engineered to function in conjunction with a sound-wave fire extinguishing system. The aggregated data were subsequently utilized to construct models capable of predicting the output characteristic (extinguishing or not) predicated on six input characteristics.

During model development, it is of paramount importance to critically review fundamental statistical properties of the data, as they can provide indispensable insights into the data distribution and variability. This allows for the identification of potential data anomalies such as outliers or missing values, which may have an impact on model performance. Furthermore, examining the statistical measures of individual variables aids in ensuring data accuracy and consistency with the expected values for that respective variable.

Table 1 presents a succinct statistical summary for all variables encompassed in the dataset, including minimum, maximum, mean values, and standard deviations. It is important to note that certain variables, such as 'fuel', are categorical and hence do not possess a significant mean or standard deviation. The 'Minimum' and 'Maximum' columns for these variables signify the classes of least and most frequent categorical variables respectively. This information assists in understanding the distribution of the categorical variables within the dataset.

Figure 1 illustrates the distribution of the variable 'fuel' among four categories: Petrol, Thinner, Kerosene, and LPG. The category demonstrating the highest frequency is 'Petrol' with a prevalence of 29.418%. Conversely, the category 'LPG' exhibits the lowest frequency, standing at 11.7647%.

Table 1 Data statistics table

	Minimum	Maximum	Mean	Deviation
Size	1	7	3.41	1.75
Fuel	-	-	-	-
Distance	10	190	100	54.8
Decibel	72	113	96.4	8.16
Airflow	0	17	6.98	4.74
Frequency	1	75	31.6	20.9
Status	0	1	0.498	0.5

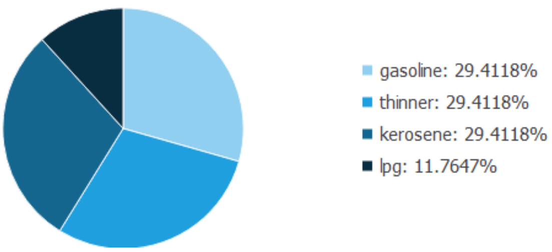

Figure 1 FUEL distribution pie chart

A correlation analysis serves as a robust empirical method for quantifying the dependencies that exist between constituent variables within a given data set. It is characterized by a numerical value, the correlation coefficient, which ranges from -1 to +1. A coefficient that tends towards the upper limit of +1 indicates a strong positive correlation. This means that an increase in one variable is usually accompanied by a corresponding increase in another. A correlation coefficient that approaches the lower limit of -1, on the other hand, indicates a strong negative correlation and signals an inverse relationship in which an increase in one variable generally triggers a decrease in the other. A correlation coefficient approaching zero, on the other hand, indicates that there is no or negligible linear correlation between the two variables under study.

In Table 2, each cell represents the calculated correlation coefficient, which makes a quantitative statement about the extent of the relationship between the corresponding pair of variables within the data set. This matrix highlights the inherent interdependence structure of the data set and promotes the formulation of insightful and rigorous inferential analyses.

Table 2 Inputs correlations

	Size	Fuel	Distance	Decibel	Airflow	Frequency
Size	1	0.431	-3.68e-11	6.8e-11	3.21e-11	6.49e-11
Fuel	0.431	1	0.176	0.176	0.176	0.176
Distance	-3.68e-11	0.176	1	-0.239	-0.707	-2.08e-15
Decibel	6.8e-11	0.176	-0.239	1	0.377	0.733
Airflow	3.21e-11	0.176	-0.707	0.377	1	-0.212
Frequency	6.49e-11	0.176	-2.08e-15	0.733	-0.212	1

A "feature trend" describes the course of the development of a certain variable over time. This progression is visually represented in Figure 2. The analysis of temporal data and the recognition of patterns facilitate the identification of trends, a crucial facet of comprehensive data analysis.

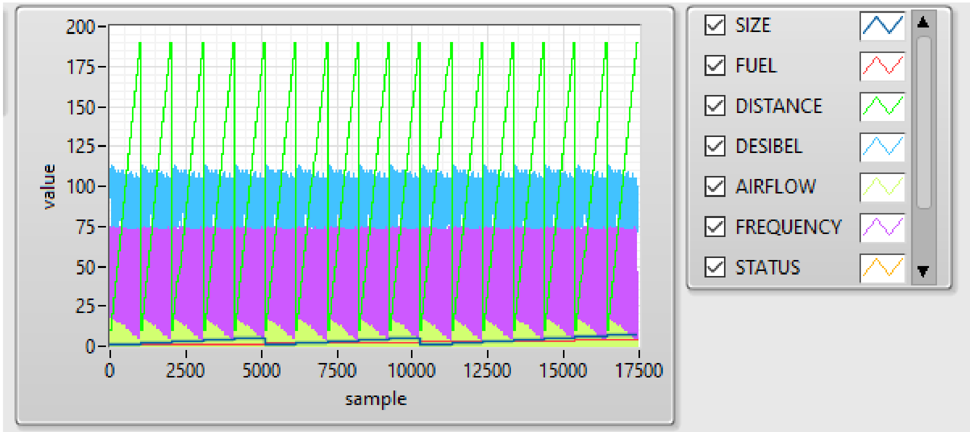

Figure 2 Feature trend

Numerous literary sources on the subject were consulted in the course of this study. These offer comprehensive insights into the processes of data collection and various other relevant scenarios. However, the focus of our work is on the development of a LabVIEW user interface and the evaluation of the effectiveness of learning algorithms.

Therefore, the specific machine learning classification techniques used in this study to analyze the above data are described in detail.

2.2. LabVIEW based Machine Learning Classifier

The software application called "LabVIEW-based Machine Learning Classifier" facilitates the creation of machine learning models in the LabVIEW programming environment. The graphically programmed interface allows users to quickly formulate and evaluate a variety of machine learning methods and algorithms. The program includes a number of pre-built machine learning classifiers that can be tailored to different scenarios, including classification, regression, and clustering. This section presents a model that uses the classification techniques of the developed LabVIEW-based machine learning classifier.

2.2.1. Artificial Neural Network

Artificial neural networks (ANNs), a sub-discipline of machine learning, draw inspiration from the structural and functional aspects of the human brain. The theoretical foundations for ANNs were laid in 1943 by McCulloch and Pitts [38], who constructed a mathematical model describing the neuronal activities of the brain. Subsequently, Hebb [39] proposed a mechanism of reinforcement-based learning to explain the learning processes of the human brain. Subsequently, Rosenblatt [40], [41] presented a computational model for the processing elements of the brain, which he called 'perceptrons', and thus provided the impetus for a thorough investigation of ANNs.

The aim of ANN's research is to develop machine learning systems based on a biological model of the brain, focusing in particular on the bioelectrical activity of the brain's neurons. This paves the way for the development of systems that are able to learn and adapt to new situations, much like the human brain. ANNs have applications in a variety of fields, including image recognition, natural language processing, speech recognition, and decision-making systems. For a graphical representation of the structure of an artificial neural network, see Figure 2.

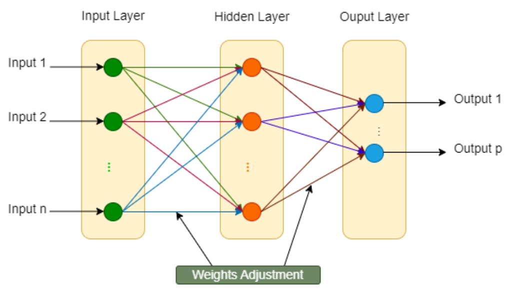

Figure 3 Basic structure of neural network.

Figure 3 contains the following integral parts:

Input layer: the first layer of the network that receives the input data and passes it on to the subsequent layer. The number of neurons in this layer corresponds to the number of features contained in the input data.

Hidden layers: These layers house the computations of the network. They consist of a collection of artificial neurons that process the input data and generate intermediate results. The number of neurons in each hidden layer, as well as the number of hidden layers themselves, can vary depending on the complexity of the problem under consideration.

Output layer: This is the last layer that produces the output of the network. It uses the intermediate results from the hidden layers and processes them further to produce the final output. The number of neurons in this layer reflects the number of classes inherent in the problem or the number of output features.

Weights: The connections between the layers, called 'weights', are critical to the learning process of the network. These weights are adjusted throughout the training phase of the network to optimize its performance and precision.

Activation function: This is a mathematical function applied to the output of each neuron that influences the final output of the neuron and consequently the output of the network.

Each layer hosts a large number of artificial neurons that process the input data to produce the final output. The architecture of the network, including the number of layers and neurons, as well as the activation function used, can be adjusted to achieve better results.

2.2.2. Support Vector Machines (SVM)

Support vector machines (SVMs) [42]–[44], a well-known category of machine learning algorithms, are mainly used for classification and regression tasks. SVMs can be roughly divided into three main categories: linear support vector machines, nonlinear SVMs, and multiclass SVMs. Linear SVMs are constructed in such a way that the instance groups of different classes separated by a hyperplane are equidistant, which allows for optimal delineation of the data. However, linear SVMs cannot handle datasets that are not linearly separable, necessitating the use of non-linear SVMs. Non-linear SVMs use kernel functions to classify non-linearly separable data. These kernel functions map the data to a higher-dimensional space and transform it into a linearly separable form. The resulting optimal hyperplane in this transformed space ensures a maximum span between the different classes. The data points, or 'vectors," closest to this hyperplane, called 'support vectors', determine the separation distance. Multiclass SVM, as the name suggests, is used to split data into multiple classes. This can be achieved by training multiple binary classifiers and merging their outputs, or by using a single classifier with multiple output values [45]–[48].

2.2.3. Logistic Regression

Logistic regression [49]–[51] is a statistical method for analyzing and modeling the relationship between a binary dependent variable and one or more independent variables. In logistic regression, the logistic function is used to estimate the probability that the outcome is 1, given a set of independent variables. The function assigns a value between 0 and 1 to each input value, which can be interpreted as the probability that the outcome is 1. The logistic regression model is trained on a set of labeled data, where each data point has a set of independent variables and a binary outcome. The model learns the relationship between the independent variables and the outcome by adjusting the parameters of the model so that the predicted probabilities match the actual outcomes as closely as possible.

The logistic function is represented by an S-shaped curve, the so-called sigmoid curve, which is defined as follows:

P(x) = 1 / (1 + e^ (-b0 - b1*x))

where P(x) is the probability that the outcome is 1 given the argument x, b0 and b1 are the parameters of the model and e is the base of the natural logarithm. The following figure shows a logistic regression model based on a sigmoid function.

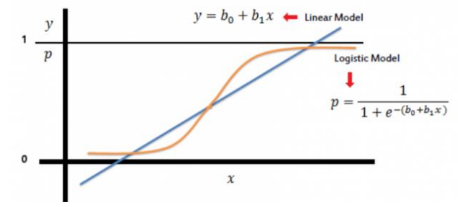

Figure 4 Logistic regression model based on the sigmoid function.

A logistic regression model is visually represented as an S-shaped curve with the probability of the dependent variable being '1' on the y-axis and the corresponding independent variable(s) on the x-axis. The curve starts at '0' on the left, moves through an inflexion point (the point of maximum slope), and ends at '1' on the right.

As the independent variable(s) increase, the curve becomes steeper, and this curve is symmetrical about the inflexion point. Therefore, the visual representation of logistic regression forms an S-shaped curve that illustrates the relationship between the independent variable(s) and the probability that the dependent variable has the value '1'.

This graphical interpretation helps to decipher the predictions of the model and understand the relationships between the variables, making it an indispensable tool for the insights gained from logistic regression.

2.3. Performance Metrics

There are several performance metrics that are used to evaluate the performance of a machine learning model [52]–[56]. In this study, the performance of the proposed system is evaluated using accuracy, precision, recall, and the F1-score. These metrics are commonly used to evaluate the performance of classification models. Accuracy is a measure of how well the system correctly predicts the class of instances. It is calculated as the ratio of correctly classified instances to the total number of instances. Precision is a measure of how well the system avoids false positives. It is calculated as the ratio of true positives to the total number of predicted positives. Recall, also known as "sensitivity", is a measure of how well the system finds all positive instances. It is calculated as the ratio of true positives to the total number of actual positive instances. The F1 score is a measure that combines both precision and recall. It is calculated as the harmonic mean of precision and recall. Using multiple metrics provides a better understanding of system performance. Understanding how well the system performs in terms of accuracy, precision, recall, and F1 score will help you identify the strengths and weaknesses of the proposed system.

Table 3 Performance metrics [57]–[60]

Abbreviation	*Description*	*Formula*
ACC	*Accuracy*	$ACC = \frac{TP + TN}{TP + FP + TN + FN}$
RCL	*Sensitivity (Recall)*	$RCL = \frac{TP}{TP + FN}$
PRE	Precision	$PRE = \frac{TP}{TP + FP}$
FSC	F-1 Score	$\mathrm{FSC} = 2 * \frac{PRE.RCL}{PRE + RCL}$

The equations in Table 3 [61], [62] allow the calculation of the metrics for accuracy, precision, recall, and F1 score using the values of true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN) from the confusion matrix (See table 4).

The Confusion Matrix [63], [64] is a tabular analysis tool that explicitly gives the number of true positives, true negatives, false positives and false negatives, all critical metrics for evaluating the performance of a binary classification model. This matrix essentially facilitates the accurate quantification of true and false predictions, allowing for a more nuanced assessment of the classifier's performance than simply assessing accuracy.

Table 4. Confusion matrix

		True Class	
		Positive	Negative
Predicted Class	Positive	TP	FP
	Negative	FN	TN

3. Experimental Results

In this study, machine learning algorithms implemented in LabVIEW are used to develop a decision support system for a sound wave-based fire extinguishing system. The system is designed to model fires caused by burning fuels using input parameters such as fuel type, flame size, decibel level, frequency, airflow, and distance. The aim of the study is to develop a system that can accurately predict the extinguishing and non-extinguishing states of a flame based on these parameters to enable more efficient use of the sound wave-based fire extinguishing system. Figure 5 show the block diagram perspectives of the proposed LabVIEW-based model. These images show the decision support system for the sound wave-based fire extinguishing system. The figures help to understand the planned design and operation of the system.

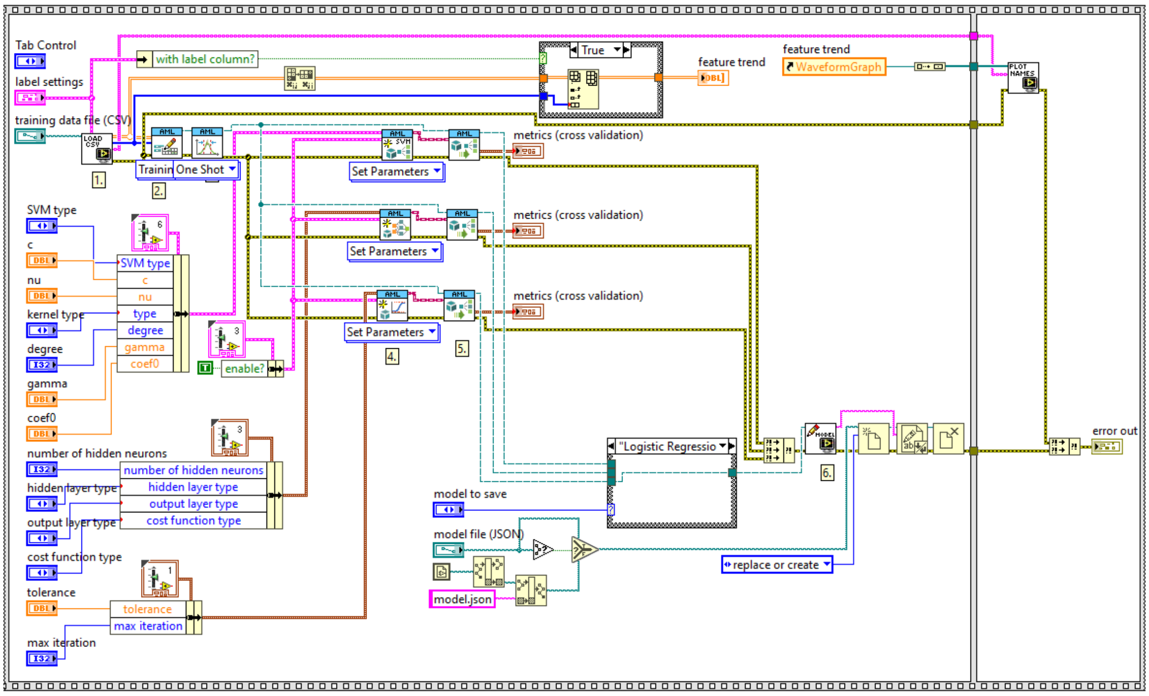

Figure 5 The block diagram of LabVIEW-based fire extinguisher model

Table 5 provides a summary of the algorithms and parameters used in the proposed model, such as the type of machine learning algorithm (e.g., neural network, SVM, logistic regression). This information can provide insight into how the model was constructed and how the different parameters were selected and used in the analysis. It can also give you an idea of how the model was trained and what factors were considered in the classification.

Table 5 Parameters setting LabVIEW-based fire extinguisher model.

Algorithm	Parameters	Values/types
SVM	SVM type	C_SVM
	Kernel type	Linear
	c	1
	nu	0,5
	degree	3
	gamma	0,5
	Coef0	0
Neural Network	Number of hidden layers	5
	Hidden layer type	sigmoid
	Output layer type	sigmoid
	Cost function type	Quadratic
Logistic Regression	Tolerance	0,001
	Max iteration	1000

Based on the values in Tables 4 and 5, various performance metrics such as accuracy, precision, detection, and F1 score were calculated. These performance metrics are a measure of the model's ability to correctly classify instances into positive and negative categories. Accuracy is the proportion of correctly classified instances out of the total number of instances. Precision is the proportion of correctly classified positive instances to the total number of predicted positive instances. Recall is the proportion of correctly classified positive instances out of the total number of actual positive instances. The F1 score is a measure of the trade-off between precision and recall. These performance measures give an overview of the performance of the model and how well it is able to classify instances into positive and negative categories. The results of these performance measures are shown in Table 6, which allows a comparison of the performance of the different algorithms used in the study.

Table 6 Performance metrics of learning algorithms

	ACC	*RCL*	*PRE*	*FSC*
SVM	0.86728	0.86096	0.86709	0.86716
ANN	**0.90893**	0.90874	0.90881	0.90885
LR	0.86836	0.86831	0.86829	0.86801

According to the developed models, the highest classification accuracy belongs to the model ANN with a value of 90.893%. The RLC, PRE, and FSC values of this model also seem to be higher than those of the other models listed in Table 6. According to this Table, the highest classification accuracy was achieved with the model ANN, with a value of 90.893%. The classification accuracy of the SVM and logistic regression models are 86.728% and 86.836%, respectively. This shows that the ANN model performs better than the other models in classifying the data correctly. These values may indicate that the ANN model correctly classifies the data and minimizes false positives and false negatives. However, it is important to note that accuracy is not always the best metric to evaluate the performance of a model. Other metrics such as precision, recall, and F1 score should also be considered.

4. Conclusion

The study presents the development of a sound wave-based fire extinguishing model using AI methods such as artificial neural networks, support vector machines, and logistic regression, implemented in LabVIEW. The model was able to classify the extinguishing and non-extinguishing states of a flame based on input parameters such as fuel type, flame size, decibel, frequency, airflow, and distance. The performance of the developed machine learning methods was analyzed and compared using performance metrics such as accuracy, precision, recall, and F1 score. The results of this study show that the highest classification accuracy of 90.893% was achieved by the neural network model, while it was 86.728% and 86.836% for the SVM and logistic regression models, respectively. This indicates that the neural network model performed best in classifying the extinguishing and non-extinguishing states of a flame. Furthermore, the use of sound wave-based models can provide a cost-effective and non-invasive alternative to traditional fire extinguishing methods. In summary, this study provides valuable insight into the potential of AI-based methods for solving fire extinguishing problems and can serve as a basis for future research in this area. The results show that the use of sound wave-based models can be an efficient and cost-effective alternative to traditional firefighting methods. Furthermore, the effectiveness of the model can be evaluated using various performance metrics. Overall, this study highlights the potential of AI-based methods in solving firefighting problems and shows how they can be a valuable tool for decision-making in firefighting systems.

Declarations

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Competing interests, The authors declare no competing interests.

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