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Determining the Extinguishing Status of Fuel Flames With Sound Wave by Machine Learning Methods

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ABSTRACT Fire is a natural disaster that can be caused by many different reasons. Recently, more environmentally friendly and innovative extinguishing methods have started to be tested, some of which are also used. For this purpose, a sound wave fire-extinguishing system was created and firefighting tests were performed. With the data obtained, as a result of 17,442 tests, a data set was created. In this study, five different machine learning methods were used by using the data set created. These are artificial neural network, k-nearest neighbor, random forest, stacking and deep neural network methods. Stacking method is an ensemble method created by using artificial neural network, k-nearest neighbor, random forest models together. Classification of extinction and non-extinction states of the flame was made with the models created with these methods. The accuracy of models in classification should be analyzed in detail in order to be used as a decision support system in the sound wave fire-extinguishing system. Hence, the classification processes were carried out through the 10-fold cross-validation method. As a result of these tests, the performance analysis of the models was carried out, and the results showed that the highest classification accuracy belongs to the stacking model with 97.06%. The classification accuracy was determined 96.58% in random forest method, 96.03% in artificial neural network model, 94.88% in deep neural network model and 92.62% in k-NN model. The performance of the methods was compared by analyzing the performance metrics of machine learning methods. Thanks to the decision support system to be obtained based on the results of the analyzes, the sound wave fire-extinguishing system can be used efficiently.

INDEX TERMS Sound wave, flame, fire, extinguishing, machine learning.

I. INTRODUCTION

Fire is a chemical reaction that breaks out with the combination of heat, fuel, and oxygen components. The heat, gas and smoke resulting from this oxidation reaction may significantly harm to human and the environment [1]. Early intervention to the fire facilitates to extinguish. However, depending on the scale of the fire and the fuel type, fire-extinguishing agents may vary. These substances in traditional fire-extinguishing techniques may leave chemical waste and harm human health [2]. Additionally, it can also cause social and economic damages [3]. In order to eliminate these impacts, researches on fire-extinguishing with renewable energy sources have been carried out. The sound waves is one of these sources. Currently, the impact of sound waves on flame and combustion behavior of fuel is a common research topic [4]. The pressure changes in the air as a result of the sound waves lead to the occurrence of airflow [5]. This airflow changes the behavior of the flame, fuel and oxygen in the environment [6]. The airflow created by the sound waves enables the fuel to spread over a wider surface. At this phase, the flame shows the tendency of spreading over a wide area together with the fuel. Fuel consumption also increases by the fuel particle oscillation due to the spread of flame and sound waves. While these stages are taking place, the air in the fire environment mixes and the amount of oxygen decreases as a result of the compression and expansion movements in the air. Through the combination of these three events,

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the flame can be extinguished [7]–[10]. Necessary frequency ranges are available for the flame to be extinguished with the sound waves [11]. Besides the frequency characteristic of sound waves, sound intensity level and the distance are also the factors having an impact on the ability to extinguish the flame [12].

Utilizing the fire characteristics, studies have been carried out to estimate the parameters necessary for the detection and extinguishing of the fire [13], [14]. The data have been obtained by examining the characteristics of the flames extinguished using sound waves. Statistical analysis and classification algorithms using these data provide information on the behaviour of the flame [15], [16]. As well as extinguishing experiments, fire data can also be obtained through sensors, cameras, and thermal cameras [17], [18]. The data obtained can be used in classification, regression, and clustering problems by utilizing machine learning algorithms [19]. Algorithms commonly used in classification problems are artificial neural network (ANN), k-nearest neighbor, regression (linear, logistic, polynomial) and tree algorithms [13], [20]–[23].

Artificial neural network (ANN), a machine learning method, is one of the most commonly used methods in classification problems. It is used for the diagnosis of diseases in medicine [24], [25], in natural language processing [26], in finance [27] and in various fields to make predictions. The k-NN method is a machine learning method that is frequently used in classification problems as well as in the solution of regression problems [28], [29]. Random forest (RF) method, on the other hand, is a kind of tree algorithm. The most significant feature distinguishing it from other tree algorithms that it contains more than one tree and it produces a strong result by evaluating the results obtained from these trees as ensemble [30]. In these methods, if the number of classifiable data is sufficient, the data set can be divided into train and test parts in order to classify the data [31]. Although the cross validation method is used to compare models, it may be necessary to divide the data set into sections in order to ensure classification accuracy in datasets with irregular distribution [32], [33]. With the studies carried out to develop the cross-validation method, the accuracy of classification results of models in evenly distributed datasets can be increased [34].

k-NN and RF methods can be used for various purposes in studies related to fires. In a study, the information obtained as a result of the spectral analysis of the images taken from the satellite was classified with k-NN and RF models, and the fire was detected on the image. As a result of the tests, a classification success between 89% and 93% has been achieved [35]. In another study, data from wireless sensors were used to identify fire points inside buildings. These data were classified with a hybrid model created from k-NN and decision tree algorithms and 70% success was achieved [36]. Studies are also carried out in the field of the Internet of Things (IoT) in order to detect fire at an early stage. The data obtained using various flame and gas sensors were classified with k-NN and decision tree algorithms. Classification success of 93.15% was obtained from the k-NN model and 89.25% from the decision tree model [37]. In another study using carbon monoxide, temperature and smoke concentration data from sensors, the probability of a fire was estimated by artificial neural networks. As a result of the tests, it was observed that the fire was detected correctly and the detection time was reduced by 32% [38]. In a study in which an IoT based detection system was created to detect and intervene in the early stage of fire, deep neural networks were used in data obtained from sensors. As a result of the tests, the classification accuracy has been achieved as 95%. In addition, the decision delay time from the detection of the fire to the response process has been reduced by 72% [39].

The dataset used in this study has been obtained from the experiments performed with the sound wave fire-extinguishing system. The objectives of this study regarding the machine learning algorithms are as follows:

1. Being able to detect the extinction and non-extinction states of the flame,
2. Determining which machine learning method can make more successfully predictions in the dataset,
3. Creating a decision support system using the essential parameters to extinguish the flame.

Based on the characteristics of the flame, the fire-extinguishing decision support system will ensure that the flame can be extinguished effectively and quickly by deciding how the sound wave fire-extinguishing system will work.

The research plan as follows: In the second chapter, data acquisition, dataset, data distributions and machine learning methods, performance metrics and correlation coefficient are explained. While the experimental results are handled in the third chapter, the discussion and the results are included in the fourth chapter.

II. MATERIAL AND METHODS

In this section, obtaining the data, the technical features of the dataset, the distribution of the data in the dataset are explained. The machine learning methods used within the scope of the study and the performance metrics required to evaluate the performance of these methods are explicated.

A. DATA ACQUISITION AND DATABASE

The dataset of the study was obtained as a result of the extinguishing tests of four different fuel flames with a sound wave extinguishing system. The sound wave fire-extinguishing system consists of 4 subwoofers with a total power of 4,000 Watt placed in the collimator cabinet. There are two amplifiers that enable the sound come to these subwoofers as boosted. Power supply that powers the system and filter circuit ensuring that the sound frequencies are properly transmitted to the system is located within the control unit. While computer is used as frequency source, anemometer was used to measure the airflow resulted from sound waves during the extinguishing phase of the flame, and a decibel meter to measure the sound intensity. An infrared thermometer was used to measure the temperature of the

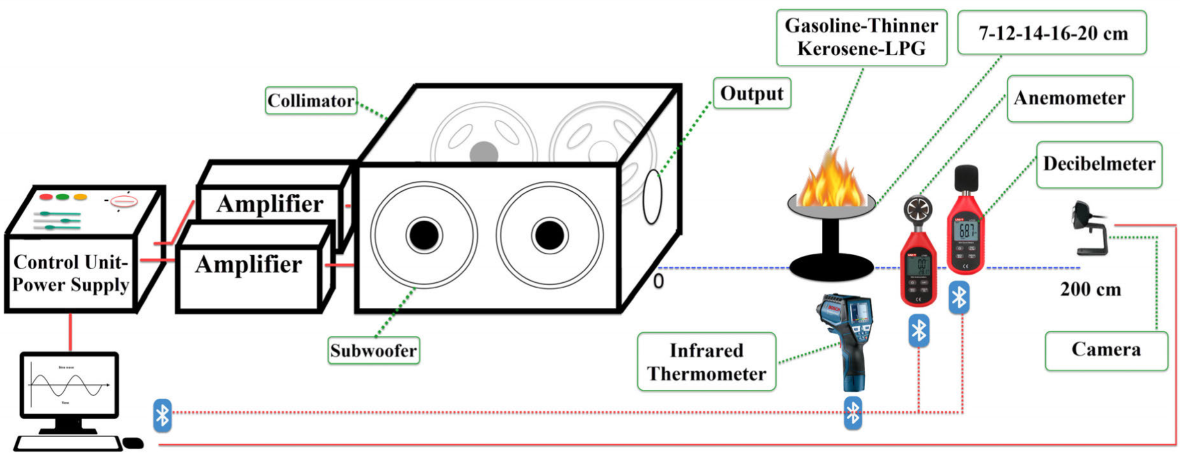

FIGURE 1. The sound wave fire-extinguishing system and the experimental setup.

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

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 2. Data features and explanations for LPG 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

flame and the fuel can, and a camera is installed to detect the extinction time of the flame. A total of 17,442 tests were conducted with this experimental setup. The experiments are planned as follows:

1. Three different liquid fuels and LPG fuel were used to create the flame.
2. 5 different sizes of liquid fuel cans are used to achieve different size of flames.
3. Half and full gas adjustment is used for LPG fuel.
4. While carrying out each experiment, the fuel container, at 10 cm distance, was moved forward up to 190 cm by increasing the distance by 10 cm each time.
5. Along with the fuel container, anemometer and decibel meter were moved forward in the same dimensions.
6. Fire extinguishing experiments was conducted with 54 different frequency sound waves at each distance and flame size.

The experiments were carried out in a fire chamber specially established for the research in which the sound wave flame system was placed. The sound wave fire-extinguishing system and the experimental setup are shown in Figure 1.

Throughout the flame extinguishing experiments, the data obtained from each measurement device was recorded and a dataset was created. The dataset includes the features of fuel container size representing the flame size, fuel type, frequency, decibel, distance, airflow and flame extinction. Accordingly, 6 input features and 1 output feature will be used in models. The explanation of a total of seven features for liquid fuels in the dataset is given in Table 1, and the explanation of 7 features for LPG fuel is given in Table 2.

The status property (flame extinction or non-extinction states) can be predicted by using six features in the dataset. Status and fuel features are categorical, while other features are numerical. 8,759 of the 17,442 test results are the non-extinguishing state of the flame. 8,683 of them are the extinction state of the flame. According to these numbers, it can be said that the class distribution of the dataset is almost equal.

B. ARTIFICIAL NEURAL NETWORK

Artificial neural networks are frequently used for the solution of classification problems [40]. An artificial neural network structure includes the input layer, hidden layer and output layer. Thanks to the connections between these layers, the learning of the model takes place [41]. The layers of the artificial neural network can be summarized as follows:

1. Input layer: This is the layer where the input data is given to the network. It contains as many neurons as the number of features to be used for class prediction in the dataset.
2. Hidden Layer: It is located between the input layer and the output layer. The learning of the model takes place through the connections between the input, hidden and output layers. In order for the model to make the best prediction, the number of neurons should be optimally determined. The hidden layer can be determined one or more.
3. Output Layer: It is the layer that contains as many neurons as the number of classes. The data classified in the model is labeled.

There are 6 neurons in the input layer, 100 neurons in the hidden layer, and 2 neurons in the output layer of the ANN model created in this study. In the training of the model, the activation function is ReLU (Rectified linear unit), the optimization function is Adam, the number of iterations is 200 and the learning coefficient is 0.0001.

C. K-NEAREST NEIGHBOR

k-NN is a machine learning algorithm which is able to classify by calculating the closest distances between data within training data [42]. Based on an integer k, the distance of an object to its k neighbors is calculated and classified. The way that the k-NN algorithm works is as follows:

1. An integer k is determined (number of nearest neighbors),
2. The distances of new objects to be classified according to a point are calculated,
3. The k closest neighbors are considered according to the distances, and the data are assigned to the closest k neighbor,
4. The chosen class is determined as the predicted class.

Different distance measurement methods are used to determine the distances between objects [43]. In the training of the model, the k value was determined as 5. Euclidean distance is used in order to find the distance between objects. Euclidean distance is calculated as in equation (1).

$$D(a, b) = \sqrt{\sum_{i=1}^{n} (a_i - b_i)} \tag{1}$$

In equation (1), D represents the distance between objects. n represents the number of iterations, while a and b represent the objects to be classified.

D. RANDOM FOREST

RF is a machine learning method which is able to classify the training data by placing it in nodes in sub-trees. RF consists of many decision trees. A query is performed on each node in the trees, and the result of these queries is placed in a node. It is very popular as a consequence of its low computational load and classification accuracy [44]. The classification steps of RF algorithm are as follows:

1. Random samples are selected from the dataset.
2. The selected samples are estimated via decision tree.
3. Results from each of the decision trees are voted.
4. The most suitable class is determined based on the votes of the predictions from the trees.

It is an ensemble method with the working structure of RF [45]. Due to this feature, it has been used for the solution of the classification problem in our study. The number of decision trees in the training of the model was determined as 10 for the study.

E. DEEP NEURAL NETWORK

Recently, the requirement for developing traditional artificial neural networks, which has recently emerged through the use of big data, has led to the creation of deep neural networks [46]. The introduction of the GPU (Graphical processing unit) to reduce the computation time has increased the use of deep neural networks [47]. Due to the high number of hidden layers, the network can perform in-depth learning [48]. The working logic of deep neural networks is similar to the ANN method [49]. The DNN model created for this study has 6 neurons in the input layer, 2 hidden layers, 50 neurons in each hidden layer, and 2 neurons in the output layer. In the training process of the model, the activation function was ReLU (Rectified linear unit), the optimization function Adam, the number of iterations was 200, the learning coefficient was 0.0001, and the dropout value was 0.2.

F. STACKING

Stacking, is an ensemble classification model that can classify by combining multiple classifier results and data in datasets [50]. A meta model is created as a result of the predictions from classifiers and training of the data. In some cases, Stacking meta model may give lower results than the classifiers that compose itself. However, it is a method that generally increases the classification accuracy [51]. In this study, the Stacking meta model was created through ANN, k-NN and RF models.

G. PERFORMANCE METRICS

Within the scope of the study, confusion matrix was used to carry out the performance analysis of the models. Confusion matrix is a matrix type which facilitates the calculation of its metrics [52]. A two-class confusion matrix is integrated as a

TABLE 3. Performance metrics.

Abbreviation	Description	Formula
ACC	Accuracy	$ACC = \frac{TP+TN}{TP+TN+FP+FN}$
FSC	F-1 Score	$FSC = 2 * \frac{PRE * RCL}{PRE+RCL}$
PRE	Precision=Positive predictive value=	$PRE = \frac{TP}{TP+FP}$
RCL	Recall=Sensitivity, True positive rate	$RCL = \frac{TP}{TP+FN}$
SPC	Specificity=True negative rate	$SPC = \frac{TN}{TN+FP}$
NPV	Negative predictive value	$NPV = \frac{TN}{TN+FN}$
FPR	False positive rate	$FPR = \frac{FP}{FP+TN}$
FNR	False negative rate	$FNR = \frac{FN}{FN+TP}$

whole rather than creating separately for each model used in the study. Figure 2 shows the confusion matrix used in the study.

Performance metrics are calculated via using the values on the confusion matrix. On the matrix, TP (True positive) value indicates the number of correctly classified positive data, FP (False positive) value indicates the number of false classified positive data, TN (True negative) value indicates the number of correctly classified negative data and FN (False negative) value indicates the number of misclassified negative. Using these values, performance metrics can be easily calculated. The formulas required to calculate the performance metrics used in the study are given in Table 3.

H. CORRELATION COEFFICIENTS

Correlation refers to the direction and strength of the linear relationship between two or more variables [53]. In other words, correlation is a method utilized to show to what extent variables affect each other.

The correlation coefficient, which is a value that shows the relationship between variables, takes values between -1 and $+1$. Negative values indicate a negative correlation, while positive values indicate a positive correlation. As the correlation coefficient approaches 0, the correlation decreases, and as it moves away from 0, the correlation increases. In this case, a correlation coefficient of -1 or $+1$ means that there is a perfect relationship between the two variables [54]. The correlation coefficient is calculated via the formula in equation (2).

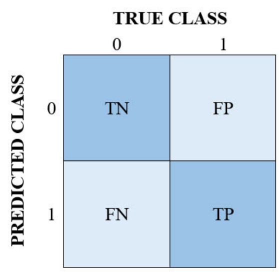

FIGURE 2. Confusion matrix.

$$r = \frac{\sum x_i y_i}{\sqrt{\sum x_i^2 \sum y_i^2}} \tag{2}$$

While r represents the correlation coefficient, x and y represent the variables.

The correlation coefficient r, regardless of negative or positive, indicates a low level of correlation between 0.01-0.29, a moderate correlation between 0.30-0.70 and

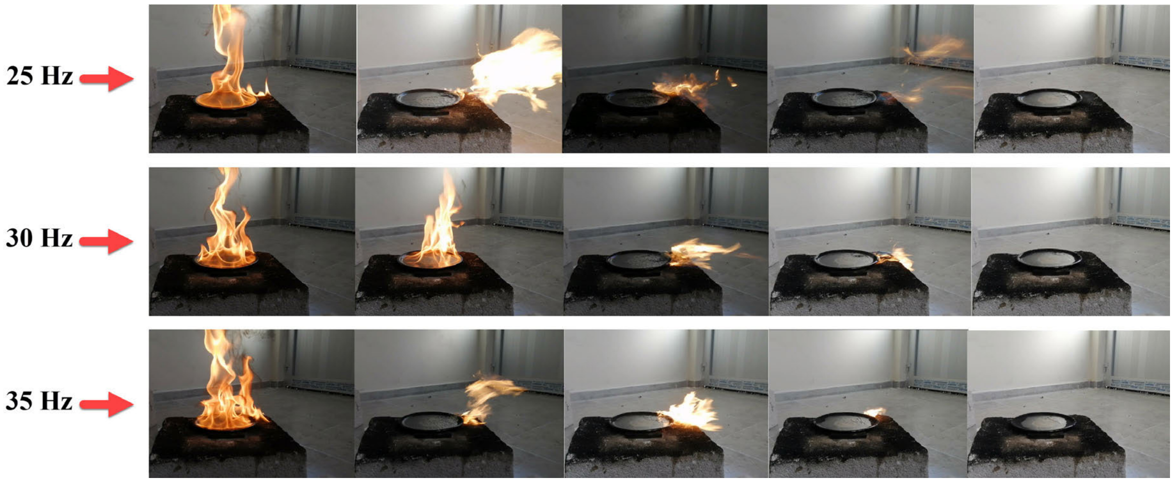

FIGURE 3. Images of fire extinguishing experiments with the sound wave flame extinguishing system.

TABLE 4. Correlation between features.

Features	Decibel	Distance	Frequency	Size	Airflow	Status
Decibel	1	-0.239	0.562	-0	0.377	-0.204
Distance	-0.239	1	0	0	-0.707	0.644
Frequency	0.562	0	1	-0	-0.212	0.244
Size	-0	0	-0	1	0	0.097
Airflow	0.377	-0.707	-0.212	0	1	-0.761
Status	-0.204	0.644	0.244	0.097	-0.761	1

a high level of correlation between 0.71- 0.99 values. A value of 0 indicates that there is no correlation between variables, and a value of 1 indicates that there is a perfect correlation between variables [55].

III. EXPERIMENTAL RESULTS

In this study, the data obtained from the experiments of extinguishing the flames emerged via various fuels with the audible flame extinguishing system were classified by ANN, k-NN, RF, stacking method created by combining these models and DNN machine learning methods. The dataset contains 17,442 number of data. The images belong to the data obtained as a result of the experiments are shown in Figure 3. In the experiments shown in the images, a 12 cm diameter fuel can and gasoline fuel were used at a distance of 1 meter, by giving a low frequency of 25, 30, 35 Hz.

The classification result is closely related to the relationship between the features and the relationship between the class feature. The features may impact the classification result positively or negatively. Correlation coefficients represents the relationship between features and class features in the dataset are shown in Table 4.

There is a low level of negative correlation between the distance and decibels. Accordingly, it can be said that the decibel value decreases as the distance increases. On the other hand, there is a moderately positive correlation between decibels and frequency. As the frequency increases, the decibel value increases. There is a high level of negative correlation between the distance and airflow values generated by sound waves. Correspondingly, as the distance increases, the air flow decreases. There is a low negative correlation between frequency and airflow. Additionally, it has been observed that the flame is extinguished at low frequencies in sound wave flame extinguishing experiments. The results revealed that all variables affect the extinction and non-extinction states of the flame.

The distribution of feature values in the dataset and the number of repetitions also have an important role in terms of analyzing the solution of classification problems. Distribution of the values belonging to the features based on the classes is shown in Figure 4. The blue color represents the non-extinction state, while the red color represents the extinction state.

Cross validation is a method that allows the classification accuracy of models to be objectively evaluated. The dataset is divided into k equal parts according to a specified value of k. Each of these pieces is separated as a test piece. The training process is carried out with the back part k-1. This process is repeated k times until each divided section is used as a test piece. The general classification success of the model is obtained by taking the arithmetic average of the classification successes obtained after each process. In this study, k value was determined as 10 as a result of the experiments. All experimental results obtained were recorded in tables separately.

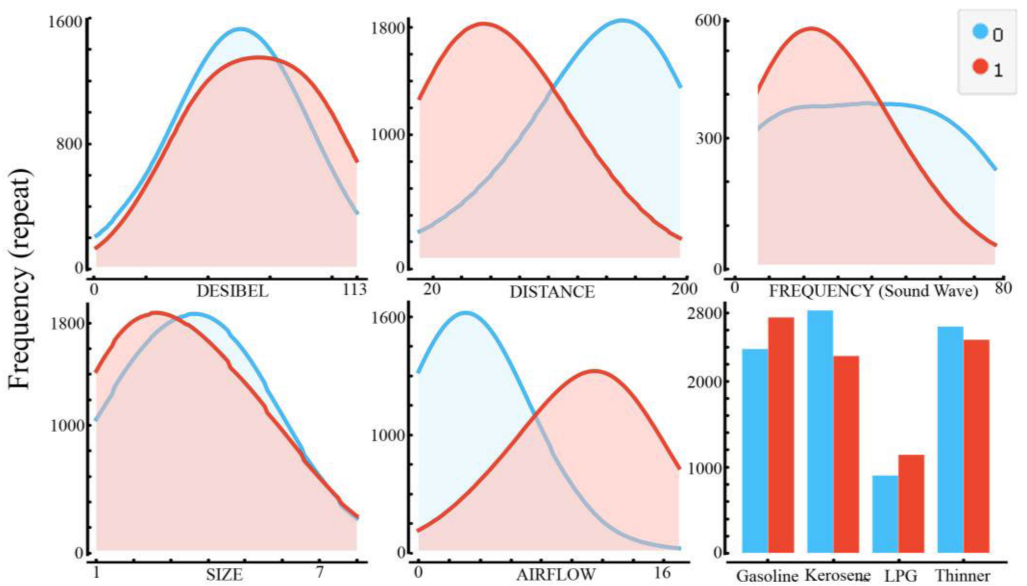

FIGURE 4. Distribution of feature values according to classes.

In Figure 5, the flow chart of the performed processes is given. A confusion matrix was used to analyze the values resulting from the classification of the test data. As a result of the calculation of the values in the confusion matrix created for each experiment with formulas, the performance metrics of the models have been obtained. The results of these performance metric for each model are also given in tables.

The confusion matrix obtained from ANN model is shown in Figure 6(a), confusion matrix obtained from k-NN model is shown in Figure 6(b), confusion matrix obtained from RF model is shown in Figure 6(c), confusion matrix obtained from DNN models shown in Figure 6(d), and lastly, the confusion matrix obtained from Stacking meta model is shown in Figure 6(e).

There are 8,759 flame non-extinction states (0), and 8,683 flame extinction states (1) in the dataset. Confusion matrix show the number of correct and incorrect classification of the models according to classes. According to Figure 6(a), the ANN model classified a total of 16,750 samples as true and 692 as false. According to Figure 6(b), the k-NN model classified 16,155 samples as true and 1,287 samples as false. According to Figure 6(c), RF model, classified 16,845 samples as true and 597 samples as false. According to Figure 6(d), DNN model classified 16,548 samples as true and 894 samples as false. According to Figure 6(e), Stacking meta model classified 16,930 samples as true and 512 samples as false. The performance metrics of the models were calculated through the data in the confusion matrix. The performance metrics obtained as a result of the calculation are shown in Table 5.

Table 5 shows that the highest classification accuracy belongs to the Stacking model with 0.9706. FSC, PRE, RCL, SPC and NPV values are higher compared to other models.

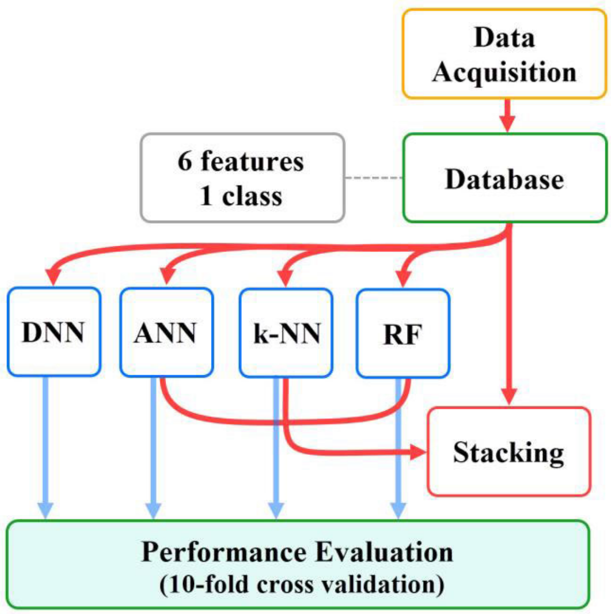

FIGURE 5. Training and test flow chart of the models.

On the other hand, FPR and FNR values are lower than other models. These metrics reveal that the Stacking model is a more successful classification model compared to the others. Classification accuracy from highest to the lowest belongs to stacking, RF, ANN, DNN, k-NN models. Table 6 shows the classification accuracy of models in percentages.

The highest classification accuracy was reached in the stacking meta model with 97.06%. The classification accuracy of the RF, ANN, DNN and k-NN models are 96.58%, 96.03%, 94.88%, and 92.62%, respectively.

TABLE 5. Performance metrics of machine learning models.

	ACC	FSC	PRE	RCL	SPC	NPV	FPR	FNR
ANN	0.9603	0.9601	0.9612	0.9590	0.9616	0.9594	0.0384	0.0410
k-NN	0.9262	0.9247	0.9399	0.9099	0.9423	0.9135	0.0577	0.0901
RF	0.9658	0.9656	0.9659	0.9653	0.9662	0.9657	0.0338	0.0347
DNN	0.9488	0.9479	0.9591	0.9370	0.9604	0.9390	0.0396	0.0603
Stacking	0.9706	0.9705	0.9712	0.9698	0.9715	0.9701	0.0285	0.0302

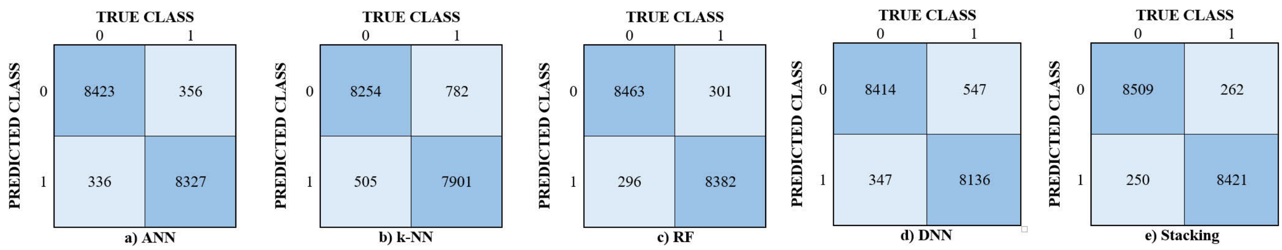

FIGURE 6. Confusion matrix of all models.

TABLE 6. Models classification accuracy (%).

	ANN	k-NN	RF	DNN	Stacking
Accuracy	96.03	92.62	96.58	94.88	97.06

IV. DISCUSSIONS AND CONCLUSION

Within the scope of this study, the data within the dataset which was obtained as a result of the sound wave flame extinguishing experiments was distributed, the correlation analysis has been conducted, and the performance evaluation of 5 different machine learning models trained with this dataset was performed. The correlation method was used to examine the relationships between features in the data set. As a result of the calculated correlation coefficients, significant relationships were found between features. The situations observed in sound wave fire-extinguishing experiments were also examined by the correlation test. The obtained values confirm the results of the experiments. It has been observed that as the frequency increases, the decibel value increases while the airflow increases as the frequency decreases. On the other hand, it has been observed that the distance affects the airflow negatively. In addition, it has been seen that all features in the dataset impact the extinction and non-extinction state of the flame. It has been determined that the frequency value of the sound is the most effective feature in extinguishing the flame.

To determine the accuracy of classifying the extinction and non-extinction state of the flame with machine learning methods, the cross-validation method was used. With this method, the objective evaluation of the extinction and non-extinction status of the flame could be made through the parameters required to extinguish the flame. As a result of the classifications by models, confusion matrices were formed. These matrices made it possible to identify correctly and incorrectly classified data samples. The performance metrics of the models were calculated by way of the matrix data. AC, FSC, PRE, RCL, SPC, NPV, FPR and FNR metrics were used in request to analyze the models' performance in depth. The results of the calculations revealed that the highest classification accuracy belongs to the stacking meta model created by combining ANN, k-NN and RF models. It was found that the classification accuracy of the stacking meta model is 97.06%. This model is followed by the RF model with a classification accuracy of 96.58%. While the classification accuracy of the ANN model has been determined as 96.03%, the DNN model has a classification accuracy of 94.88%. The lowest classification accuracy belongs to the k-NN model with 92.62%. The accuracy ranking of the models' performance metrics has also shown similarities to the ACC metric. Despite the fact that the difference between the classification accuracy of the models appear insignificant, this ratio is substantial in 17,442 amounts of data. For instance, there are 85 differences between the number of data samples correctly classified by stacking and RF models, with 0.48% difference between classification accuracy. It is of considerable importance that these models, which have the nature of decision support systems for the work of the sound wave fire-extinguishing system by using the data in the dataset, have high classification accuracy.

It has been determined that frequency range values of 10-50 Hz in the distance of 10-100 cm, frequency range values of 10-32 Hz in the distance of 100-150 cm, frequency range values of 10-28 Hz in the distance of 150-180 cm. These frequency ranges are effective flame extinguishing ranges. As a result of the experiments for liquid petroleum gas (LPG) fuel, the flame could be extinguished effectively in the frequency range of 10-45 Hz in the distance range of 10-140 cm and in the frequency range of 15-30 Hz in the distance range of 140-180 cm. Sound intensity of 85-113 dB, varying according to distance, was obtained in the frequency range of 10-50 Hz. The air flow created by the sound pressure was measured as 17 m/s at a frequency of 30 Hz at a distance of 10 cm. In addition, it has been observed that the cooling of the fuel container with the effect of air flow is almost 2 times faster than cooling under normal conditions.

To be able to quickly decide on the parameters to be used in flame extinguishing works with the sound wave flame extinguishing system, it will be possible to utilize the decision support system created with the results obtained from this study. The high number of data in the data set will also be effective in decision-making by the decision support system. In future researches, based on the results of these experiments, it is planned to create an expert system and to operate this system automatically with a sound wave fire-extinguishing system.

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