E-ISSN: 2717-3453 | P-ISSN: 2783-1442

Journal of Fuzzy Extension and Applications

www.journal-fea.com

J. Fuzzy. Ext. Appl. Vol. 4, No. 3 (2023) 217–234.

Paper Type: Research Paper

Fire Extinguishers Based on Acoustic Oscillations in Airflow Using Fuzzy Classification

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Citation:

Dirik, M. (2023). Fire extinguishers based on acoustic oscillations in airflow using fuzzy classification. *Journal of fuzzy extension and applications, 4*(3), 217-234.

Received: 09/01/2023 Reviewed: 12/02/2023 Revised: 19/03/2023 Accepted: 05/04/2023

Abstract

Fire is a natural disaster that poses a profound existential threat to humanity. It has traditionally been fought with conventional methods, which, unfortunately, are often fraught with limitations and potential environmental damage. Given these limitations, there is an urgent need for research into novel firefighting methods. Sound wave-based firefighting systems, an emerging solution, show promising potential in this regard.

The current study uses an extensive data set derived from numerous experimental trials of sound-wave-based firefighting. Based on this extensive dataset, we have developed a sound wave technology-based fire suppression model that includes five different fuzzy logic methods: Fuzzy Rough Set (FRS), Fuzzy K-Nearest Neighbors (FNN), Fuzzy Ownership K-Nearest Neighbors (FONN), Fuzzy-Rough K-Nearest Neighbors (FRNN), and Vaguely Quantified K-Nearest Neighbors (VQNN).

The main objective of these models is to accurately distinguish between the extinguished and non-extinguished states of a flame. This classification is based on a number of intrinsic model parameters, such as the type of fuel, the size of the flame, the decibel level, the frequency, the airflow, and the distance.

To evaluate the classification effectiveness of the models, a number of statistical methods were used, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Kappa Statistics (KP), and Mean Square Error (MSE).

Our analysis yielded promising results, with the models FRS, FNN, FONN, FRNN, and VQNN achieving classification accuracies of 93.12%, 96.66%, 95.56%, 96.35%, and 96.89%, respectively. These results confirm the high accuracy of the proposed model in classifying fire data and underline its practical applicability.

Keywords: Acoustic oscillations, Fire suppression, Fuzzy classification, Firefighting techniques, Sound wave acoustic.

1 | Introduction

Fire, adversity originating either from natural phenomena or human lapses, necessitates proactive detection and early intervention [1]. Depending on their nature, firefighting approaches potentially inflict collateral harm to both the environment and the populace [2]. Given the specialized knowledge required for fire suppression, the choice of extinguishing methodology is of paramount importance. Varying combustible materials necessitate differentiated extinguishing techniques; a singular method is seldom capable of addressing all fire types. Hence, investigations into alternative fire suppression techniques are currently in progress [3]-[5].

One such technique under scrutiny is sound wave-based fire extinguishment. This strategy exhibits a reduced likelihood of environmental or human harm and offers the advantage of reusability [1], [6]. The primary mechanism of such fire suppressants involves oxygen deprivation to the flame, achieved

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https://doi.org/10.22105/jfea.2023.401426.1291

by manipulating airflow via the compression and expansion of sound waves [7]. Empirical studies [8]-[13] have demonstrated that the pressure induced by low-frequency (30 Hz-50 Hz) sound waves can effectively extinguish flames and diminish fuel mass.

Sound waves' efficacy can vary under the influence of gravitational forces, as evidenced by their usage in spacecraft, where extinguishment is achievable within a frequency range of 60 Hz to 90 Hz [8], [14], [15]. Apart from the frequency attributes of sound waves, their intensity and propagation distance also play significant roles in fire suppression [16].

There have been concerted efforts to ascertain the requisite parameters for fire detection and suppression based on inherent fire characteristics [17]-[20]. Research exploring the properties of flames extinguished by sound waves has yielded insights into flame behavior, with statistical analysis and classification algorithms being used to interpret this data [21]. Beyond extinguishment trials, fire-related data can also be amassed through sensors, cameras, and thermal imaging devices [22]-[27].

Machine learning techniques have been instrumental in utilizing this accumulated data to tackle classification, regression, and clustering tasks [28]-[30].

Experimental trials employing the sound wave fire extinguishing technique served as the primary data source for this investigation [8], [31]-[33]. The dataset, comprising 17,442 samples, was derived from experiments varying in fuel type, frequency, distance, and flame size as parameters within the sound wave fire suppression system. Subsequently, a fuzzy-based classification model was architectured, utilizing data from an acoustically governed airflow extinguishing system to suppress liquid and gaseous fuels [8], [31]-[33]. The fuzzy classification methodology incorporated is the fuzzy roughest neighbor technique [34]-[38].

Fuzzy sets [39]-[42] and rough sets [43]-[45] represent natural computational paradigms designed to negotiate the qualities of imperfect data and knowledge akin to human cognition. Simultaneously, they characterize elements corresponding to certain and probable concepts to facilitate concept estimation, even amidst information scarcity. Such approximations are realized by grouping objects into certain and probable concept categories. Dubois and Prade were pioneers in proposing a hybrid Fuzzy Rough Set (FRS) model in [44], which has since found successful applications across various domains, predominantly in machine learning.

The K-Nearest Neighbor (KNN) method is a recognized classification approach that assigns a test object to the decision class most frequently represented among its K nearest neighbors [46]-[48]. A specific extension of the KNN technique to fuzzy set theory, termed Fuzzy Nearest Neighbor (FNN), was developed [49]. This not only considers the relative distance of each neighbor but also allows an object to possess partial membership in multiple classes. However, the FNN algorithm encounters challenges when dealing with insufficient data [35], [50], [51]. The 'fuzzy rough ownership function' software was developed to remedy this. The term 'fuzzy rough' may be misleading as it bears no relation to the core components of fuzzy set theory, specifically the lower and upper approximations of a decision class.

In this research, we validate that those fuzzy approximations derived from a test object's nearest neighbors can accurately predict its classification. Our most trustworthy predictions stem from output classifications based on sound wave-dependent parameters. The uniqueness of the VQRS technique lies in its use of natural language quantifiers like 'some' and 'most,' enhancing the model's resistance to categorization errors [52].

The study's objectives center around distinguishing extinguished and non-extinguished flame states, identifying the algorithm with superior predictive ability, and constructing a model with essential parameters for flame suppression. The sound wave-based extinguishing model governs the fire suppression system based on flame characteristics, ensuring quick and efficient extinguishment. *Fig. 1* outlines the proposed classification model's structure and parameters, which include input parameters, classifiers, and output.

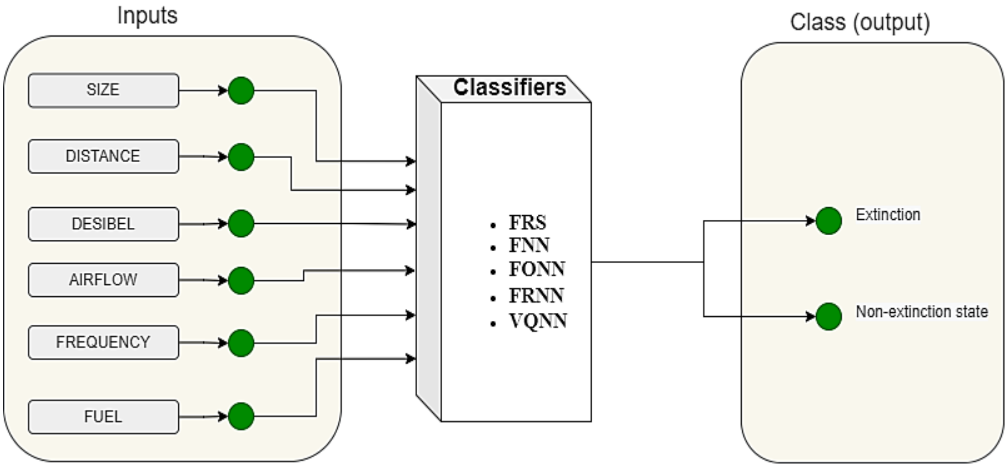

Fig. 1. Diagram of a fuzzy classification model for an acoustically regulated airflow-based fire suppression system.

The machine learning component often termed the 'black box', forms the intermediate element in this system, learning and making decisions (see *Fig. 1*). Effective models reliably predict new inputs' outcomes. With modern computing power and data digitization, supervised learning algorithms are increasingly crucial across various applications. A model is deemed interpretable if its predictive reasoning is comprehensible. While standards exist for assessing a classification system's performance using metrics like accuracy, Receiver Operating Characteristic Curve (ROC) area, and Root Mean Square Error (RMSE), a universally accepted interpretability measure is yet to be established. There's no perfect equilibrium between interpretability and performance in classification systems; simpler ones, while less powerful, are more easily understood.

The rest of this paper is structured as follows: Section 2 discusses materials and methods, including the dataset, classification algorithms, and performance metrics. Section 3 presents experimental results, and Section 4 concludes with interpretations and conclusions.

2 | Methodology

This section elucidates the methodology employed for data acquisition, the technical attributes of the dataset, and the data distribution within the dataset. It further delineates the classification strategies implemented in this research and the performance metrics essential for appraising the efficacy of these classification methodologies.

2.1 | Data Acquisition

The utilized dataset [8], [31]-[33] encompasses data derived from trials of the sonic extinguisher on four distinct fuel flames. The system comprises four subwoofers situated within the collimator enclosure, with an aggregate power of 4,000 watts and a pair of amplifiers designed to magnify and direct the sound towards these subwoofers. The control unit houses the power supply, responsible for system energizing, and the filter circuit, ensuring the accurate transmission of sound frequencies. While the computer functioned as the frequency source, an anemometer and decibel meter were employed to monitor the airflow engendered by sound waves during the flame-extinguishing phase. A camera was mounted to chronicle the flame extinction timeframe, and an infrared thermometer was used to gauge the temperature of the flame and fuel container. This experimental arrangement facilitated the conduct of a total of 17,442 trials. *Fig. 2* illustrates the comprehensive layout of the employed acoustic wave-based flame suppression system.

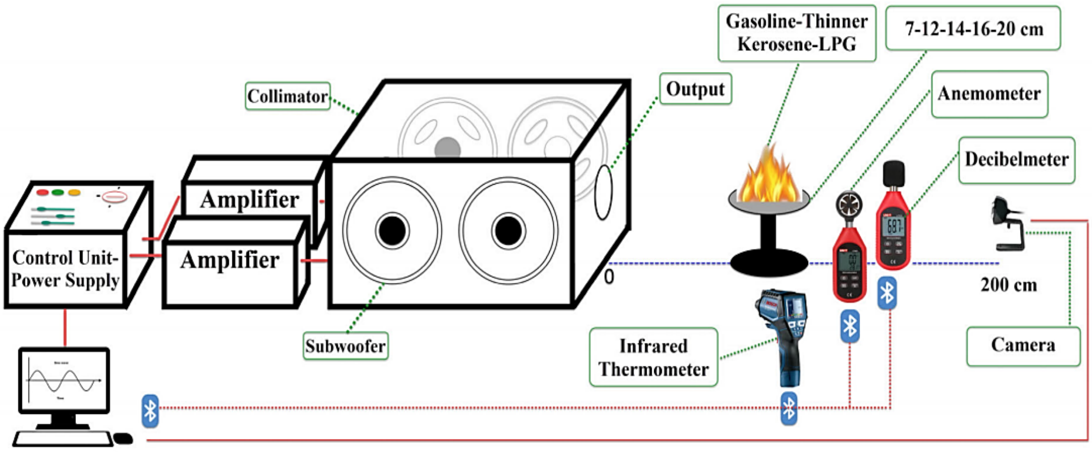

Fig. 1. Fire-extinguishing system using sound waves and its experimental setup [36].

Experiments were carried out in a specially designed fire chamber, which housed the sonic flame apparatus. Throughout the course of flame extinguishing studies, data were amassed into a dataset, encompassing parameters such as fuel tank size, flame size, fuel type, frequency, decibels, distance, airflow, and flame extinction. Thus, the models are formulated based on six input features and one output feature. The output feature—flame extinction or non-extinguishment—should be prognosticated based on the six aforementioned features in the dataset. *Table 1* and *Table 2* illustrate the utilized dataset's general data distribution and statistical specifics, respectively, whereas *Fig. 3* presents a histogram of the employed data.

Table 1. Characteristics and descriptions of the data in the utilized dataset.

Attributes	Descriptions of Features	Min.	Max.	Mean	StdDev
SIZE	7, 12, 14, 16, 20 cm recorded as 7 cm=1, 12 cm=2, 14 cm=3, 16 cm=4, 20 cm=5	1	7	3.412	1.751
DISTANCE	10 - 190 cm	10	190	100	54.774
DESIBEL	72 - 113 dB	72	113	96.379	8.164
AIRFLOW	0 - 17 m/s	0	17	6.976	4.736
FREQUENCY	1-75 Hz	1	75	31.611	20.939

Table 2. Features and interpretations of the data in the employed dataset.

Attributes	Descriptions of Features	Label	Count	Weight
FUEL	Fuel type	Gasoline	5130	5130
		Kerosene	5130	5130
		Thinner	5130	5130
		LPG	2052	2052
STATUS	Extinction or non-extinction state	0	8759	8759
		1	8683	8683

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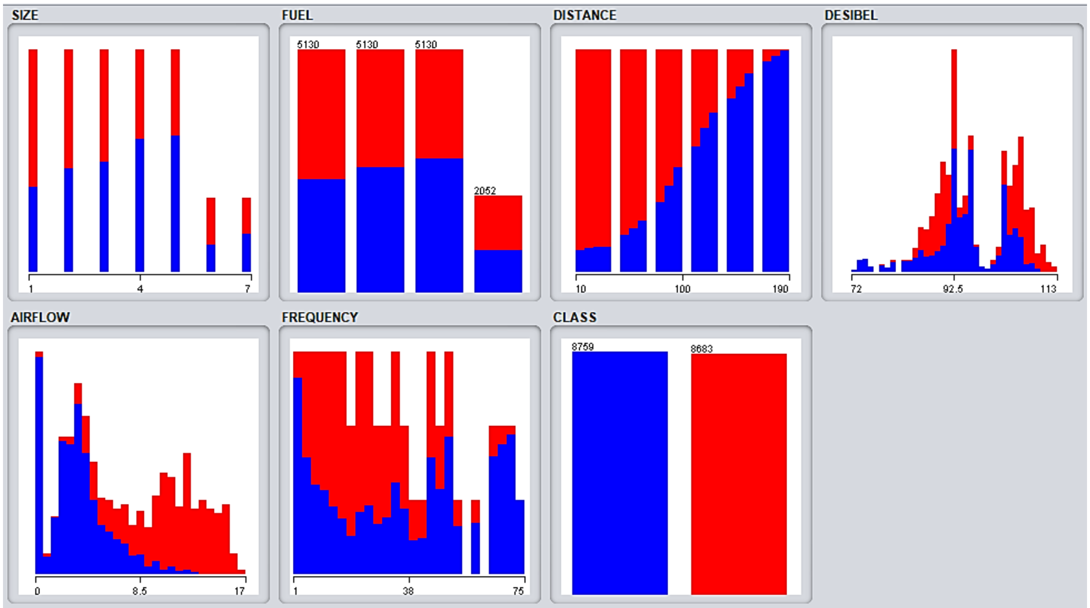

Fig. 2. Histogram of the data used.

2.2 | Fuzzy Classifier

This section introduces the classification algorithms in our model. These classifiers use fuzzy logic definitions for upper and lower approximations, eliminating the need for traditional fuzzy relations. This fuzzy logic method was chosen for its strength in dealing with uncertain and vague data and its ability to interpret degrees of truth rather than absolute truths, which meets our model's need for a detailed understanding of the data.

The selection criteria based on these fuzzy approximations represent the links between the accuracy of the premises and the resulting outcomes. In this way, fuzzy logic can efficiently handle complex decision-making processes common in the real world.

2.2.1 | Fuzzy rough set theory

We derive FRSs by amalgamating fuzzy logic methods, capable of extracting imprecise structures, with data mining techniques. The FRS approach utilizes strategies such as inference from missing data, knowledge base reduction, data mining, and rule extraction to prepare insufficient, ambiguous, and incomplete data for analysis. It has the aptitude to handle inconsistent and incomplete data, which poses a significant challenge for rule extraction and classification. FRSs are versatile tools and find applications in various artificial intelligence methods, including uncertainty resolution, pattern recognition, image analysis, feature extraction, classification, rule reduction, and machine learning. These techniques have found utility across various domains, such as medicine, finance, rule simplification, dispute resolution, and feature selection [53]-[60]. Rough clustering incorporates fundamental concepts such as decision systems (tables), consciousness, approximate clustering, reductions, core ideas, rough membership, and attribute dependence. The concept of rough sets enables the pragmatic application of rule reduction and classification techniques. *Fig. 4* provides a schematic representation of the rough set.

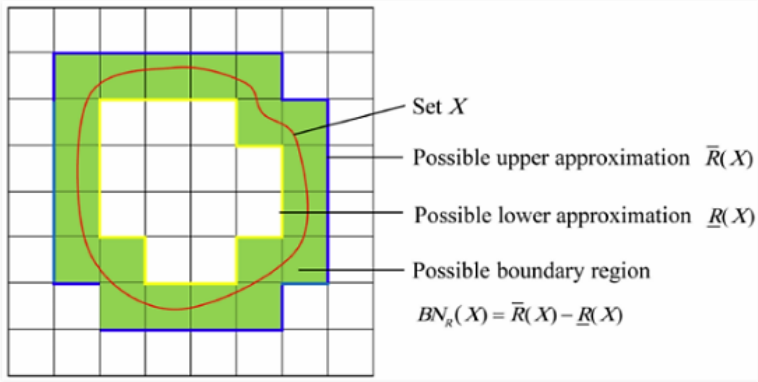

Fig. 3. Schematic representation of the rough set [66].

Assume U as a finite collection of objects, referred to as the universe, and A as a finite set of associated attributes. The pair S = (U, A) represents an information system. Each attribute A is defined by a function a: U ⟶ Va, where Va is the domain of the attribute for each a in A. Any subset B ⊆ A delineates a distinctness relation, termed INDs (B), as expressed in *Eq. (1)*.

$$IND_s\ B) = \left\{ x, y) \in U^2 \forall_a \in B_a\ x) = a(y)\right\}. \quad (1)$$

If a set X cannot be precisely distinguished utilizing attributes of B ⊆ A, and the system calculates the lower and upper approximations of X, the following can be posited: the B-lower approximation set symbolized as $\underline{R}$ X), represents the set of objects that unequivocally belong to the element X (refer to *Eq. (2)*).

$$\underline{R}\ X) = \left\{X_i \in U|\ [X_i]_{INDs(R)} \subset X\right\}. \quad (2)$$

X constitutes a set of objects that could potentially be part of the B-upper approximation, represented by

$$\bar{R}\ X) = \left\{X_i \in U|\ [X_i]_{INDs(R)} \cap X \neq 0\right\}. \quad (3)$$

The notation $\overline{R}(X)$ (refer to *Eq. (3)*).

2.2.2 | Fuzzy k-nearest neighbors

The FNN technique [49] is implemented to classify test subjects based on their proximity to a certain number of neighbors and their degree of association with this group. This strategy was designed using fuzzy-rough fuzziness, which enhances the classification performance of the conventional KNN method [49], [61]. The proposed method preserves the simplicity and nonparametric characteristics of the classic KNN algorithm. Contrary to the conventional technique, our proposed approach doesn't require knowledge of the optimal K value. Additionally, the sum of class confidence values, constructed as fuzzy-rough values, doesn't always add up to one [62], [63]. The pseudocode for this algorithm is provided in *Algorithm 1*.

Algorithm 1. The fuzzy rough nearest neighbor's algorithm (C is the total number of class, q ε (1,∞) is an index of fuzziness controls) [50].

INPUT: (a) Training data $\{x_i \mid i = 1,2,\dots,n\}$ with fuzzy class labels.
(b) The test pattern $\boldsymbol{y}$.
ALGORITHM:
Compute $\boldsymbol{\kappa}$.
$FOR\ c = 1\ to\ C$
Set $o(c)$ as zero
END FOR
FOR $i = 1$ to n
Determine squared weighted distance

$$d = \sum_{j=1}^{N} \kappa_j (y_j - x_{ij})^2 \ between\ y\ and\ x_i.$$

FOR $c = 1$ to C

$$L\!: o(c) = o(c) + \frac{1}{|\mathscr{X}|} \mu_{C_c}(x_i) exp\left(-d^{1/(q-1)}\right)$$

END FOR
END FOR
Crisp class label of $\boldsymbol{y}$ is j where $o(j) = max\{o(1), o(2), \dots, o(C)\}$.
OUTPUT: (a) Class label of $\boldsymbol{y}$.
(b) Class confidence values $o(c)\ for\ all\ c$.

2.2.3 | Fuzzy ownership k-nearest neighbors

The fuzzy rough ownership function represents an amalgamation of the FNN algorithm with principles derived from FRS theory [51], [64], [65]. It effectively addresses both "fuzzy uncertainty," arising from competing classes, and "brute uncertainty," stemming from inadequate information about objects or features. Unlike the FNN method, this function takes into account all training objects, eliminating the need to specify a predetermined number of neighbors. This is due to the fact that training objects situated farther away do not significantly impact the result. This aligns with the Parzen window approach [66], where all objects within a certain distance are considered, rather than just the k closest training objects. *Algorithm 2* [35] presents the pseudocode for this algorithm.

Algorithm 2. The fuzzy-rough ownership nearest neighbour algorithm.

Input: X, the training data; A, the set of conditional features; $\mathcal{C}$, the set of decision classes: y, the object to be classified.
Output: Classification for y
begin
foreach $a \in \mathbb{A}$ **do**
$\kappa_a = |X|/2\sum_{x\in X} \parallel a(y) - a(x) \parallel^{2/(m-1)}$
end
$N \leftarrow |X|$
foreach $C \in \mathscr{C}$ **do** $\tau_C(y) = 0$
foreach $x \in N$ **do**
$d = \sum_{a\in A} \kappa_a (a(y) - a(x))^2$
foreach $C \in C$ **do**

$$\tau_c(y) += \frac{c(x) \cdot exp\left(-d^{1/(m-1)}\right)}{|N|}$$

end
end
output arg $\max_{c \in e} \tau_C(y)$
end

2.2.4 | Fuzzy-rough k-nearest neighbors

The proposed method, known as Fuzzy Roughest Nearest Neighbors (FRNN), leverages the concept of nearest neighbors to construct fuzzy lower and upper approximations of decision classes. Subsequently, it classifies test patterns based on their membership within these approximations. This method offers a comprehensive solution by integrating fuzzy brute approaches with FNN principles. The corresponding pseudocode for this algorithm is outlined in *Algorithm 3* [35].

Algorithm 3. The fuzzy-rough nearest neighbour algorithm.

```
Input: X, the training data; C, the set of decision classes; y, the object to be classified
Output: Classification for y
begin
        N ← getNearestNeighbours (y, K)
        τ ← 0, Class ← ∅
    foreach C ∈ 𝒞 do
        if ((R ↓ C)(y) + (R ↑ C)(y))/2 ≥ τ then
            Class ← C
            τ ← ((R ↓ C)(y) + (R ↑ C)(y))/2
        end
    end
    output Class
end
```

This method summarizes the proposed technique that combines fuzzy brute approximations with the FNN approach. The approach is based on the premise that the upper and lower approximations of a decision class computed from the nearest neighbors of a test object y provide useful information for predicting whether the test object belongs to that class. In particular, a high value of (R↓C) (y) indicates that all neighbors of y belong to class C, while a high value of (R↑C) indicates that at least one neighbor belongs to that class. Since τ is initialized to zero in line (2), a classification for y is always determined. The decision class is determined using the best combination of the lower and upper fuzzy approaches, or the information from the lower and upper fuzzy approaches is used to determine membership in this class.

2.2.5 | Vaguely quantified k-nearest neighbors

The Vaguely Quantified Nearest Neighbor (VQNN) method has been applied for data classification, leveraging the notion of overall similarity within each class [37]. This approach incorporates linguistic quantifiers such as "most" and "some" to facilitate its operations. By employing a set of fuzzy quantifiers (Qu, Ql) to represent "most" and "some," respectively, the upper and lower approximations of class C are utilized to assign a class label to the target instance y [52], [67]. The upper and lower approximations of vaguely quantified rough sets are characterized as follows:

I. The upper approximation of C, denoted as (R↑C), represents the set of instances that "most" likely belong to class C.
II. The lower approximation of C, denoted as (R↓C), includes instances that "some" likely belong to class C.

These approximations serve as vital components in the VQNN method, facilitating the classification process based on the overall similarity within each class. Vaguely quantified rough sets' upper and lower approximations are characterized as follows:

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$$\left(\left(R \downarrow^{Q_u} C\right)(y)\right) = Q_u\left(\frac{\sum_{x} \in x\min(Rx, y), C(x)}{\sum_{x} \in xR(x, y)}\right). \quad (4)$$

$$\left(\left(R \uparrow^{QI} C\right)(y)\right) = Q_I\left(\frac{\sum_{x\in x} \min(Rx, y), C(x)}{\sum_{x} \in xR(x, y)}\right). \quad (5)$$

2.3 | Performance Metrics

The main objective of performance evaluation is to verify the efficiency of the algorithms used and the system's applicability. To substantiate a classification method, comparing the resulting values with empirical observations is necessary. The performance indices for a sound wave-based fire extinguishing system include a confusion matrix, sensitivity, specificity, False Positive Rate (FPR), the balanced classification rate, and the Matthews correlation coefficient. The confusion matrix for the binary classifier is shown in *Table 3* [68]. Sophisticated metrics are used to investigate the relationships between these indicators. *Table 4* shows the measurements used to evaluate performance.

Table 3. Confusion matrix.

Predicted Negative		Predicted Positive
Actual negative	True Negative (TN)	False Positive (FP)
Actual positive	False Negative (FN)	True Positive (TP)

In the structure of the confusion matrix, True Positive (TP) symbolizes the quantity of positively labeled data that has been accurately classified, whereas False Positive (FP) represents the quantity of positively labeled data that has been inaccurately classified. True Negative (TN) signifies the quantity of negatively labeled data that has been correctly classified, and False Negative (FN) corresponds to the quantity of negatively labeled data that has been inaccurately classified. Moreover, parameters such as sensitivity, specificity, accuracy, F-measure, and Area Under the Curve (AUC) were considered for the methods proposed in this study. *Table 4* lays out the mathematical expressions for the performance assessment metrics employed in this research.

Table 4. Performance metrics.

Abbreviation	Description	Formula	References
ACC	Accuracy	$ACC = \frac{TP + TN}{TP + FP + TN + FN}$	[69]-[71]
RCL	Sensitivity (Recall)	$RCL = \frac{TP}{TP + FN}$	[70], [71]
SPC	Specificity	$SPC = \frac{TN}{FP + TN}$	[70], [71]
PRE	Precision	$PRE = \frac{TP}{TP + FP}$	[70], [71]
FSC	F-1 Score	$FSC = 2 * \frac{PRE \cdot RCL}{PRE + RCL}$	[70], [71]
MCC	Mathews Correlation Coefficient	$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$	[72]

Table 4. Continued.

Abbreviation	Description	Formula	References
AUC	Area Under the Curve	$AUC = \frac{1}{2} \cdot (RCL + SPC)$	[73]
KP	Kappa statistics	$KP = \frac{\text{(observed accuracy - expected accuracy)}}{1 - \text{ expected accuracy}}$	[74]
MAE	Mean Absolute Error	$MAE = \frac{1}{N} \sum_{i=1}^{N} \lvert \hat{\theta}_i - \theta_i \rvert$	[73]
RMSE	Root Mean Square Error	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\hat{\theta}_i - \theta_i\right)^2}$	[73]

The ROC is described by the area under the receiver operating characteristic curve (AUC). In a threshold classifier, the ROC curve can be used to examine the balance between the rate of TPs and FPs (True Positive Rate (TPR) or FPR). Precision and recall are the most important parameters to consider in the context of unbalanced data (i.e., the F-score). Precision indicates the degree of agreement and closeness between the scale of the results and the expected response. In addition to the above indices, the AUC is also suggested as a performance measure. The AUC is a graphical representation of the FPR and the TPR at different thresholds. Since the AUC is not dependent on a threshold, it serves as a more reliable measure of comprehensive performance than accuracy [70].

3 | Experimental Results

In the present research, algorithms based on fuzzy logic (FRS, FNN, FONN, FRNN, and VQNN) were employed to suppress fires ignited by flaming fuels, thereby developing an acoustic extinguishing system. The interrelation between the features might influence the classification outcome either positively or negatively. Furthermore, the investigation of sonic flame extinguishing revealed that all parameters impact the status of the flame, either extinguishing it or leaving it burning. The distribution of feature values and the count of duplicates within the dataset also significantly contribute to the study of the classification problem. *Fig. 3* exhibits the distribution of feature values per class.

Cross-validation serves as an approach for objectively assessing the accuracy of model categorization. The dataset is partitioned into 'k' equal segments, contingent on the specified 'k' value. Subsequently, data undergo cross-validation. Each of these segments is isolated as a testing sample. The 'k-1' rear component is utilized during the training phase. This procedure is conducted 'k' times until every component has served as a test sample. The overall classification success of the model is the arithmetic mean of the classification success of each procedure. Based on the experiments within this study, the 'k' value was established at 10. All resulting test outcomes were tabulated. The process flow diagram is displayed in *Fig. 5*.

A confusion matrix was implemented to analyze the values resulting from the test data classification. Computation of the values in the confusion matrix, formulated for each test using formulas, provided the models' performance metrics. The tables present the outcomes of these performance metrics for each model.

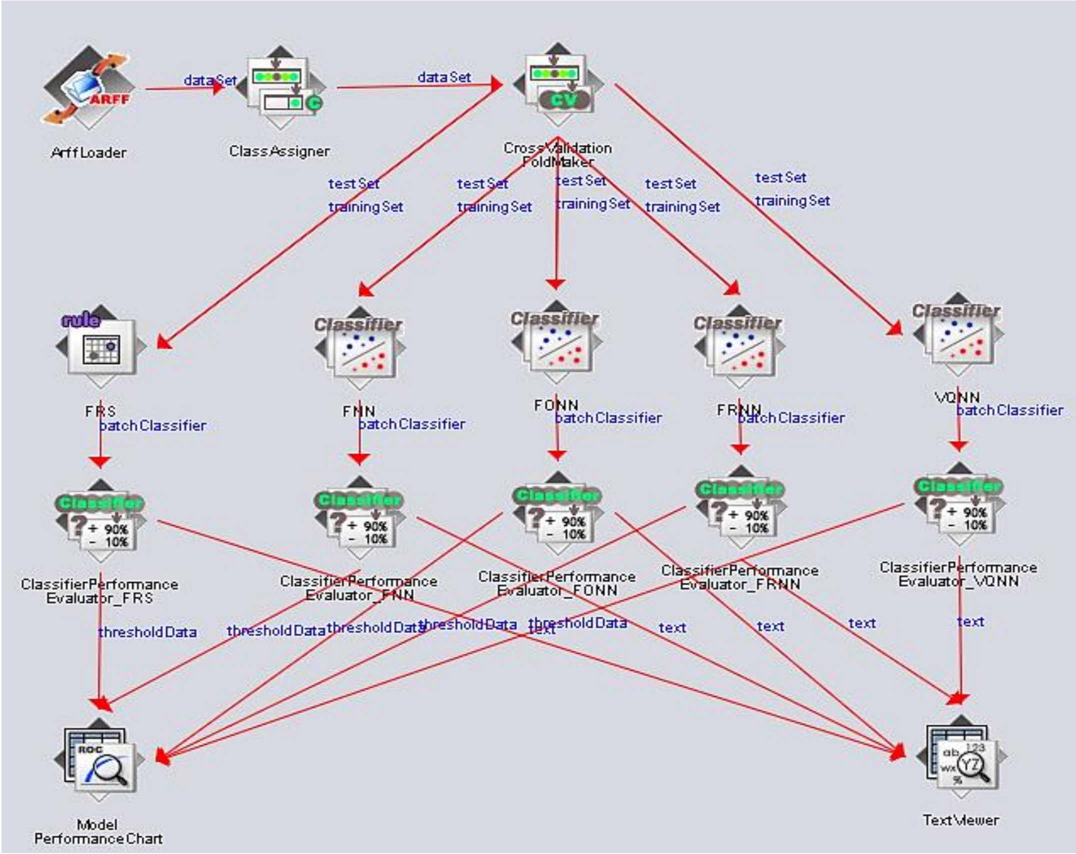

Fig. 5. Flowchart of the process in the knowledge flow of the environment.

A series of tests were performed to prove the effectiveness of the proposed method. A comparative analysis was performed to evaluate the classification performance of fuzzy and fuzzy rough techniques. The confusion matrix of the proposed models (FRS, FNN, FONN, FRNN, and VQNN) are shown in *Fig. 6*.

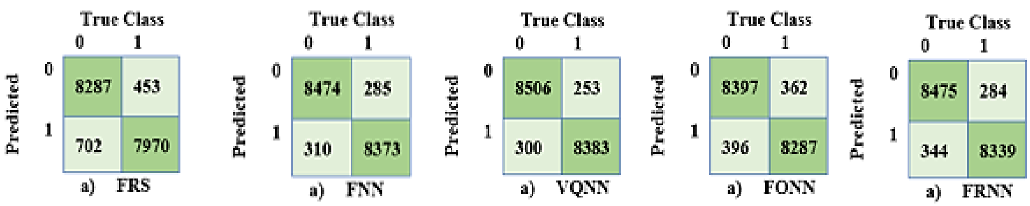

Fig. 6. Confusion matrix of proposed models.

The performance measures of the models were derived from the information extracted from the confusion matrix. The calculated performance measures are presented in *Table 5* and *Table 6*, providing a comprehensive evaluation of the model's performance.

Additionally, *Fig. 7* depicts a graphical representation of the performance metrics, offering a visual overview of the model's effectiveness. This graphical representation aids in understanding and comparing the performance of different models, enabling the identification of patterns, trends, and areas for improvement.

By utilizing the information from the confusion matrix and presenting the performance measures in tabular and graphical formats, a comprehensive evaluation of the models' performance is achieved, providing valuable insights into their efficacy and aiding in informed decision-making.

Table 5. Performance metrics of proposed fuzzy-based models.

	TP Rate	FP Rate	PRE	RCL	FSC	MCC	ROC Area	PRC Area	Class
FONN	0.959	0.046	0.955	0.959	0.957	0.913	0.991	0.991	0
	0.954	0.041	0.958	0.954	0.956	0.913	0.991	0.992	1
FRNN	0.968	0.04	0.961	0.968	0.964	0.928	0.995	0.995	0
	0.96	0.032	0.967	0.96	0.964	0.928	0.995	0.996	1
VQNN	0.971	0.035	0.966	0.971	0.969	0.937	0.996	0.995	0
	0.965	0.029	0.971	0.965	0.968	0.937	0.996	0.996	1
FNN	0.967	0.036	0.965	0.967	0.966	0.932	0.966	0.95	0
	0.964	0.033	0.967	0.964	0.966	0.932	0.966	0.95	1
FRS	0.948	0.081	0.922	0.948	0.935	0.868	0.973	0.966	0
	0.919	0.052	0.946	0.919	0.932	0.868	0.974	0.967	1

TP is the situation where both the actual and expected values are 1. TN occurs when both the actual and expected values are 0. FP are situations where the actual value is 0, but the expected value is 1. FN occurs when the actual value of a variable is 1, and our expected value is 0. ACC is a measure of how often the classifier makes a correct classification. The TPR indicates the percentage of TP values the classifier correctly predicts. The true negative rate indicates the percentage of TN values the classifier correctly predicts. The FPR is the percentage of individuals whose predicted value is 1 while the true value is 0. The FN rate is the percentage of individuals whose predicted value is 0 while the actual value is 1. Precision is the degree to which predictions from all classes are correct.

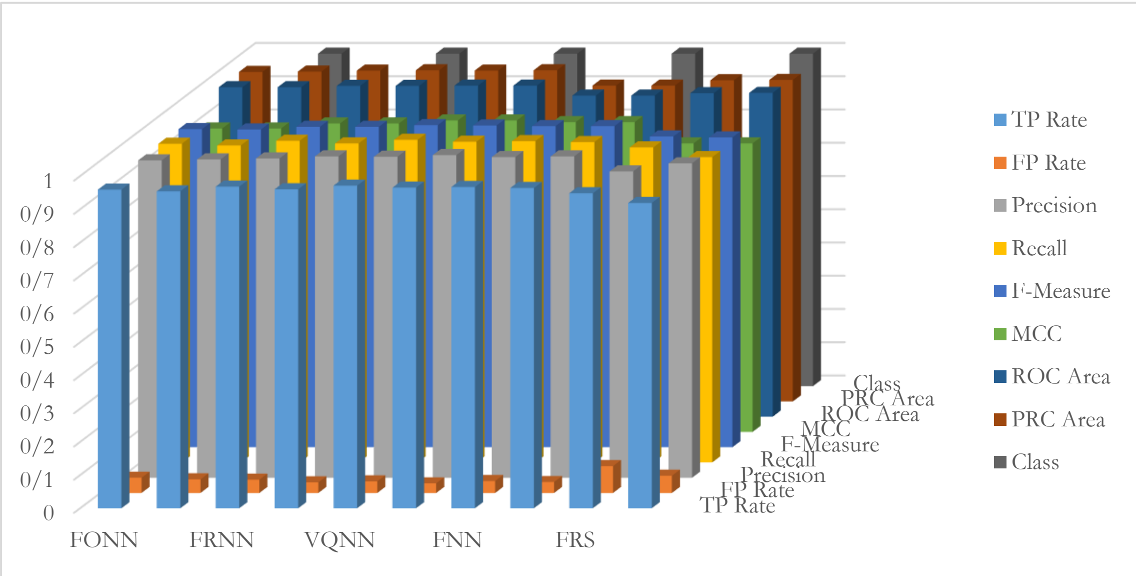

Fig. 4. Graphical representation of the performance metrics.

The Kappa Statistic quantifies the actual performance of the classifier. In other words, the kappa score of a model is high if there is a significant discrepancy between its accuracy and its error rate. The F-score is the harmonic mean of the ratio of TPs (recall) to accuracy (precision). It is a measure of how well the classifier performs and is often used to compare classifiers.

Table 3. Performance metrics of performed models.

	ACC	KP	MAE	RMSE
FRS	93.12%	0.8673	0.0742	0.2253
FNN	96.66%	0.9318	0.0341	0.1847
FONN	95.56%	0.9131	0.0594	0.1861
FRNN	96.35%	0.928	0.1108	0.2335
VQNN	96.89%	0.9366	0.0457	0.1567

In machine learning models, the RMSE is often used to measure the difference between expected and actual values. The RMSE is the standard deviation of the prediction error. In other words, it measures the distance between the errors and the data points on the regression line. Mean Absolute Error (MAE) is a measure of the difference between two continuous variables. MAE is a linear variable that measures the average number of errors in a set of predictions, regardless of their direction, with each error having the same weight on the mean.

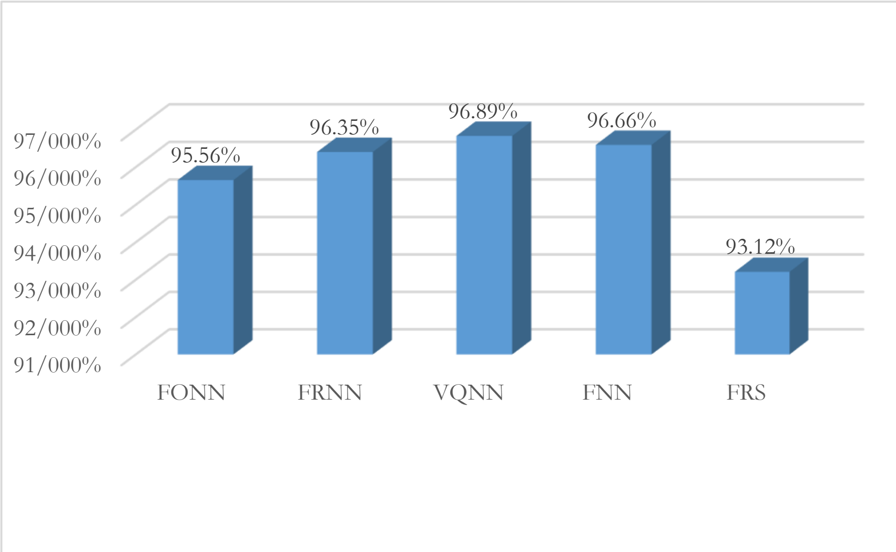

Fig. 8. Algorithms classification accuracy (%).

As seen in *Table 6* and *Fig. 8*, the VQNN model achieved the highest classification accuracy of 96.89%. These metrics show that the VQNN model is a more effective classifier than the others. The classification accuracy of the VQNN, FNN, FRNN, FONN, and FRS models ranges from the highest to the lowest. *Fig.* 8 shows the percentage classification accuracy of the models. The classification accuracy of the FNN, FRNN, FONN, and FRS models is 96.66%, 96.35%, 95.56%, and 93.12%, respectively. The ROC curve is an important metric for classification performance. The area under the ROC probability curve (AUC) represents the degree of separability or metric. The greater the class difference, the greater the AUC. The optimal threshold for class separation must be determined to create the ideal ROC curve. The optimal ROC curve is also developed once the ideal F1 score is found by experimenting with different thresholds. The AUC value measures the ability of a model to discriminate between classes. The higher the AUC value, the more accurately the model predicts that 0s will be 0s and 1s will be 1s. *Fig. 9* shows the ROC curve created using the proposed models.

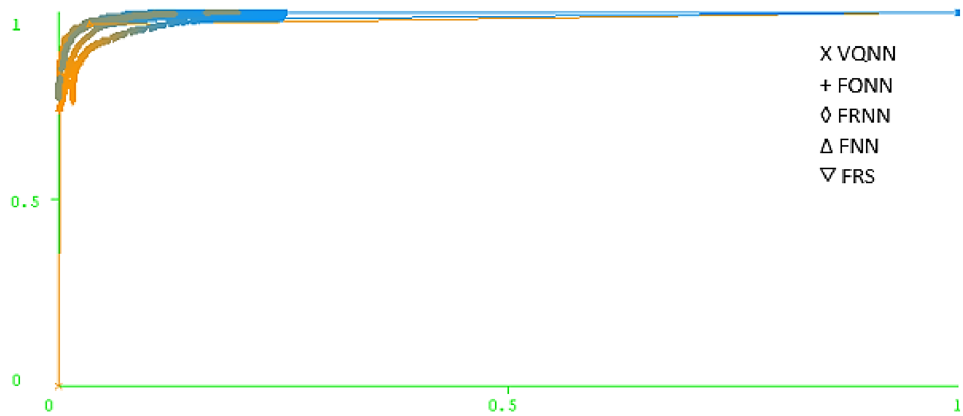

Fig. 9. ROC Curve for all models

The purpose of this curve was to evaluate the balance between sensitivity and selectivity. The area under the ROC curve represents the ROC value. This number also describes the performance of the model. A lower value on the x-axis means fewer FPs and more TNs. The values on the y-axis increase when the number of TPs and FNs decreases. The ROC curve is created by graphing the number of TPs versus the number of FPs for each categorization level. *Table 7* shows the general comparison of the previous results in a single table and the algorithm's performance.

Table 7. Analysis of the performance of the algorithm ((1) rules.Roughset, (2) fuzzy.FuzzyNN, (3) fuzzy.FuzzyOwnershipNN, (4) fuzzy.FuzzyRoughNN, (5) fuzzy. VQNN).

	(1) Rules.Ro |	(2) Fuzzy	(3) Fuzzy	(4) Fuzzy	(5) Fuzzy
Percent correct	93.12 |	96.66v	95.56v	96.35v	96.89v
Kappa statistics	0.87 |	0.93v	0.91v	0.93v	0.94v
MAE	0.07 |	0.03*	0.06*	0.11v	0.05*
RMSE	0.23 |	0.18*	0.19x	0.23v	0.16*
Relative Absolute Error (RAE)	15.02 |	6.68 *	11.91*	22.29v	9.12 *
TPR	0.95 |	0.97v	0.96v	0.97v	0.97v
FPR	0.08 |	0.03*	0.05*	0.04*	0.03*
True negative rate	0.92 |	0.97v	0.95v	0.96v	0.97v
False negative rate	0.05 |	0.03*	0.04*	0.03*	0.03*
Recall	0.95 |	0.97v	0.96v	0.97v	0.97v
F measure	0.93 |	0.97v	0.96v	0.96v	0.97v
Matthews correlation	0.87 |	0.93v	0.91v	0.93v	0.94v
Are under ROC	0.97 |	0.97*	0.99v	1.00v	1.00v
Elapsed time testing	0.84 |	41.68	5.90v	5.83v	5.83v
User CPU time testing	0.83 |	7.51v	5.82v	5.77v	5.78v

4 | Conclusion and Future Works

Based on fuzzy set theory, this study used a combination of classification and estimation techniques - VQNN, FNN, FRNN, FONN, and FRS. We constructed fuzzy-based classification models for acoustic flame extinguishing systems using a dataset of 17,442 tests.

We used five fuzzy logic models to classify flames' extinguishing and non-extinguishing states accurately. The VQNN model, which integrates lower and upper techniques with natural language quantifiers, performed equivalently to FNN and FRNN models under standard conditions.

Through cross-validation, we evaluated the accuracy of these models and created confusion matrices to identify correctly and incorrectly classified data samples. VQNN had the highest classification accuracy of 96.89%, followed by FNN (96.66%), FRNN (96.35%), FONN (95.56%), and FRS (93.12%).

Our results led to the development of a decision support system that enables faster parameter selection for flame-extinguishing tests. We believe that our approach, especially the sonic flame fire extinguishing system, can minimize the damage to electronic equipment and the environmental impact.

In the future, we plan to refine these models using different datasets and explore the integration of fuzzy methods for coarse feature selection. There are opportunities to reduce computational complexity and extend these models to data with missing values.

However, our study has limitations. The models are based on a specific data set, and their performance may vary for different flame types, conditions, or extinguishing systems. Moreover, despite its advantages, fuzzy logic leads to complexity in interpretation and computation, especially for larger data sets.

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