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Machine Learning Models with Neutrosophic Numbers for Cloud Security Analysis and Smart Grid Control of Renewable Energy

Ahmed E Fakhry1,2, Mamdouh Gomaa2, Ahmed A. Metwaly3, Ahmed Abdelhafeez1

1 Computer Science Department, Faculty of Information Systems and Computer Science, October 6th University, Giza, 12585, Egypt ahmed.e.csis@o6u.edu.eg; aahafeez.scis@o6u.edu.eg

2 Department of Computer Science, Faculty of Information Technology, Amman Arab University, 11953, Amman, a.elsharkawy@aau.edu.jo; m.gomaa@aau.edu.jo

3 Department of Computer Science, Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Egypt, a.metwaly23@fci.zu.edu.eg.

Abstract:

Machine learning (ML) enables difficult tasks to be completed independently. In a smart grid (SG), computers and mobile devices may make it easier to monitor security, control interior temperature, and perform routine maintenance. The ability of smart grids to identify cyberattacks is essential for assessing the operation's reliability and availability. This essay emphasizes the integrity of cyberattacks using fake data in the physical layers of smart grids (SGs). This paper analyzes data transmission security and proposes a novel approach to smart grid energy management. Here, renewable energy sources are used to assess the smart grid network's energy efficiency, and the network has been monitored for cloud computing security assessments. We use an interval trapezoidal neutrosophic number model to deal with uncertainty information and rank the best ML model under different evaluation matrices. We use the k-nearest neighbor with k= 3 to 12. The CoCoSo method is used to rank ML models.

Keywords: Neutrosophic Sets; Uncertainty; Renewable Energy; Cloud Security; Smart Grid.

1. Introduction

As the demand for more efficient energy distribution and use grows, the significance of smart grid management systems (SGMS) has dramatically increased. By integrating ML techniques with SGMS, cost, and energy efficiency might be significantly increased.[1]. Using machine learning (ML) algorithms that learn from past data and real-time monitoring, the SGMS ensures optimal performance, optimizes energy usage, and provides accurate projections. An adaptable power framework with negative evaluation capabilities, energy executives, exchange and estimating, SG monetary exchanges, energy trading, and the use of renewable power sources in conjunction with an SG board are some suggestions for enhancing the way SG blockchain technology and digital currencies are presented. This might result in a more advantageous load profile and financial gain.[2], [3].

Furthermore, earlier researchers modified the blockchain's calculations to allow online client networks to use Bitcoin to operate in commercial hubs and energy frameworks in safer ways [2]. The journalists' energy architecture also makes use of advanced cash. One of the major technological developments of the twenty-first century is the growth of the Internet of Things.[4], [5]. The Internet of Things (IoT) is a network of interconnected devices, software, and physical hubs that facilitate the sharing and exchange of information. The "IoT" refers to the exchange of data between various devices and frameworks.[6].

The necessity for energy supply security and the growing global energy demand have prompted a persistent attempt to move away from the traditional power generating grid and toward a flexible SG that incorporates renewable energy sources (RES). Demand and supply have changed dynamically over time, creating a highly difficult climate. Real-time data is gathered because a network system of connecting procedures to numerous variables may be used to operate and analyze devices, systems, and processes regularly in this environment.[7], [8].

Cybersecurity measures are used to stop ransomware, malware, and viruses from causing disruptions and data breaches.[9], [10]. When correctly deployed, these measures can help smart grid operators identify and address network vulnerabilities before they cause damage. Protecting smart grids from potential terrorist attacks, espionage efforts, and vulnerabilities caused by weather, malfunctioning equipment, and human error is crucial.[11]. The two most widely used protocols are the Transport Control Protocol (TCP), which ensures that even long, fragmented communications are correctly reassembled at their destination (for purposes like efficiency or media sharing), and the Internet Protocol (IP), which identifies devices and systems.[12].

One of the most important and pervasive activities about real-world applications during the last few decades has been MCDM. Numerous attempts to evaluate the RESs using various MCDM techniques have been made in the literature. Even still, conventional methods of decision-making are insufficient for handling the ambiguous data that typically arise during energy planning procedures. Because of its adaptability and efficiency in handling circumstances where the information at hand is ambiguous or insufficient, the fuzzy set (FS) concept has motivated researchers worldwide[13]. Atanassov [14] introduced the idea of the intuitionistic fuzzy set (IFS), an extension of FSs that is more suited to handling fuzziness and uncertainty than Zadeh's suggestion of FS.

However, contradictory and ambiguous information presented in real-world scenarios cannot be handled by the notions of FSs and IFSs; they can only handle partial and unclear information. Smarandache [15], [16] Has intended the neutrosophic set (NS) to better handle such information. A strong general formal framework that reduces the sets from a philosophical perspective, NS is a component of neutrosophy, which investigates the genesis, nature, and extent of neutralities as well as their interactions with various ideational spectra. The term "neutrosophy" refers to the "knowledge of neutral thought," and the word "neutral" represents the primary difference between FSs, IFSs, and their logic[17], [18].

2. Proposed Model

This section shows the operations of interval-valued trapezoidal neutrosophic number (IVTNN) [19], [20]And steps of the CoCoSo method to rank the ML models under different criteria.

$$K^L = \left\{\left(Y, T_K^L(Y), I_K^L(Y), F_K^L(Y)\right); y \in Y\right\} \tag{1}$$

$$T_K^L(Y) \subset [0,1], I_K^L(Y) \subset [0,1], F_K^L(Y) \subset [0,1] \tag{2}$$

We can define the trapezoidal neutrosophic fuzzy numbers such as:

$$T_K^L(Y) = \left(t^{L1}{}_K(Y), t^{L2}{}_K(Y), t^{L3}{}_K(Y), t^{L4}{}_K(Y)\right)Y \to [0,1] \tag{3}$$

$$F_K^L(Y) = \left(f^{L1}{}_K(Y), f^{L2}{}_K(Y), f^{L3}{}_K(Y), f^{L4}{}_K(Y)\right)Y \to [0,1] \tag{4}$$

$$T_K^L(Y) = \left(i^{L1}{}_K(Y), i^{L2}{}_K(Y), i^{L3}{}_K(Y), i^{L4}{}_K(Y)\right)Y \to [0,1] \tag{5}$$

$$0 \le t^{L4}{}_K(Y) + i^{L4}{}_K(Y) + f^{L4}{}_K(Y) \le 3 \tag{6}$$

$$K^L = \left\{\left((a_1, a_2, a_3, a_4), (b_1, b_2, b_3, b_4), (c_1, c_2, c_3, c_4)\right) > Y \to [0,1]\right\} \tag{7}$$

We can show the neutrosophic operations such as:

$$k_1 = \left\{\begin{matrix} \left([(a_1, a_2, a_3, a_4), (\overline{a_1}, \overline{a_2}, \overline{a_3}, \overline{a_4})]; T_{n_1}\right), \\ \left([(b_1, b_2, b_3, b_4), (\overline{b_1}, \overline{b_2}, \overline{b_3}, \overline{b_4})]; I_{n_1}\right), \\ \left([(c_1, c_2, c_3, c_4), (\overline{c_1}, \overline{c_2}, \overline{c_3}, \overline{c_4})]; F_{n_1}\right) \end{matrix}\right\} \tag{8}$$

$$K_2 = \left\{\begin{matrix} \left([(d_1, d_2, d_3, d_4), (\overline{d_1}, \overline{d_2}, \overline{d_3}, \overline{d_4})]; T_{n_2}\right), \\ \left([(e_1, e_2, e_3, e_4), (\overline{e_1}, \overline{e_2}, \overline{e_3}, \overline{e_4})]; I_{n_2}\right), \\ \left([(f_1, f_2, f_3, f_4), (\overline{f_1}, \overline{f_2}, \overline{f_3}, \overline{f_4})]; F_{n_2}\right) \end{matrix}\right\} \tag{9}$$

$$K_1 \oplus K_2 = \begin{pmatrix} \left[\begin{pmatrix} a_1 + d_1 - a_1 d_1, a_2 + d_2 - a_2 d_2, \\ a_3 + d_3 - a_3 d_3, a_4 + d_4 - a_4 d_4 \end{pmatrix}, \begin{pmatrix} \overline{a_1} + \overline{d_1} - \overline{a_1}\overline{d_1}, \overline{a_2} + \overline{d_2} - \overline{a_2}\overline{d_2}, \\ \overline{a_3} + \overline{d_3} - \overline{a_3}\overline{d_3}, \overline{a_4} + \overline{d_4} - \overline{a_4}\overline{d_4} \end{pmatrix} \right], \\ \left[\begin{matrix} (b_1 e_1, b_2 e_2, b_3 e_3, b_4 e_4), \\ (\overline{b_1}\overline{e_1}, \overline{b_2}\overline{e_2}, \overline{b_3}\overline{e_3}, \overline{b_4}\overline{e_4}) \end{matrix} \right], \\ \left[\begin{matrix} (c_1 f_1, c_2 f_2, c_3 f_3, c_4 f_4), \\ (\overline{c_1}\overline{f_1}, \overline{c_2}\overline{f_2}, \overline{c_3}\overline{f_3}, \overline{c_4}\overline{f_4}) \end{matrix} \right] \end{pmatrix} \tag{10}$$

$$K_1 \otimes K_2 = \begin{Bmatrix} \left[\begin{matrix} (a_1 d_1, a_2 d_2, a_3 d_3, a_4 d_4), \\ (\overline{a_1}\overline{d_1}, \overline{a_2}\overline{d_2}, \overline{a_3}\overline{d_3}, \overline{a_4}\overline{d_4}) \end{matrix} \right], \\ \left[\begin{pmatrix} b_1 + e_1 - b_1 e_1, b_2 + e_2 - b_2 e_2, \\ b_3 + e_3 - b_3 e_3, b_4 + e_4 - b_4 e_4 \end{pmatrix}, \begin{pmatrix} \overline{b_1} + \overline{e_1} - \overline{b_1}\overline{e_1}, \overline{b_2} + \overline{e_2} - \overline{b_2}\overline{e_2}, \\ \overline{b_3} + \overline{e_3} - \overline{b_3}\overline{e_3}, \overline{b_4} + \overline{e_4} - \overline{b_4}\overline{e_4} \end{pmatrix} \right], \\ \left[\begin{pmatrix} c_1 + f_1 - c_1 f_1, c_2 + f_2 - c_2 f_2, \\ c_3 + f_3 - c_3 f_3, c_4 + f_4 - c_4 f_4 \end{pmatrix}, \begin{pmatrix} \overline{c_1} + \overline{f_1} - \overline{c_1}\overline{f_1}, \overline{c_2} + \overline{f_2} - \overline{c_2}\overline{f_2}, \\ \bar{c} + \overline{f_3} - \overline{c_3}\overline{f_3}, \overline{c_4} + \overline{f_4} - \overline{c_4}\overline{f_4} \end{pmatrix} \right] \end{Bmatrix} \tag{11}$$

$$\varphi k_1 = \begin{pmatrix} \left[\begin{pmatrix} 1 - (1 - a_1)^{\varphi}, 1 - (1 - a_2)^{\varphi}, \\ 1 - (1 - a_3)^{\varphi}, 1 - (1 - a_4)^{\varphi} \end{pmatrix}, \begin{pmatrix} 1 - (1 - \overline{a_1})^{\varphi}, 1 - (1 - \overline{a_2})^{\varphi}, \\ 1 - (1 - \overline{a_3})^{\varphi}, 1 - (1 - \overline{a_4})^{\varphi} \end{pmatrix} \right], \\ \left[(b_1^{\varphi}, b_2^{\varphi}, b_3^{\varphi}, b_4^{\varphi}), (\overline{b_1}^{\varphi}, \overline{b_2}^{\varphi}, \overline{b_3}^{\varphi}, \overline{b_4}^{\varphi}) \right], \\ \left[(c_1^{\varphi}, c_2^{\varphi}, c_3^{\varphi}, c_4^{\varphi}), (\overline{c_1}^{\varphi}, \overline{c_2}^{\varphi}, \overline{c_3}^{\varphi}, \overline{c_4}^{\varphi}) \right] \end{pmatrix} \tag{12}$$

$$k_1^{\varphi} = \begin{pmatrix} \left[(a_1^{\varphi}, a_2^{\varphi}, a_3^{\varphi}, a_4^{\varphi}), (\overline{a_1}^{\varphi}, \overline{a_2}^{\varphi}, \overline{a_3}^{\varphi}, \overline{a_4}^{\varphi}) \right], \\ \left[\begin{pmatrix} 1 - (1 - b_1)^{\varphi}, 1 - (1 - b_2)^{\varphi}, \\ 1 - (1 - b_3)^{\varphi}, 1 - (1 - b_4)^{\varphi} \end{pmatrix}, \begin{pmatrix} 1 - \left(1 - \overline{b_1}\right)^{\varphi}, 1 - \left(1 - \overline{b_2}\right)^{\varphi}, \\ 1 - \left(1 - \overline{b_3}\right)^{\varphi}, 1 - \left(1 - \overline{b_4}\right)^{\varphi} \end{pmatrix} \right], \\ \left[\begin{pmatrix} 1 - (1 - c_1)^{\varphi}, 1 - (1 - c_2)^{\varphi}, \\ 1 - (1 - c_3)^{\varphi}, 1 - (1 - c_4)^{\varphi} \end{pmatrix}, \begin{pmatrix} 1 - (1 - \overline{c_1})^{\varphi}, 1 - (1 - \overline{c_2})^{\varphi}, \\ 1 - (1 - \overline{c_3})^{\varphi}, 1 - (1 - \overline{c_4})^{\varphi} \end{pmatrix} \right] \end{pmatrix} \tag{13}$$

We show the steps of the CoCoSo method.

Experts create the decision matrix as

$$Y = \begin{bmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{bmatrix} \tag{14}$$

Compute the criteria weights using the average method.

Normalize the decision matrix for beneficial and non-beneficial criteria.

$$H_{ij} = \frac{y_{ij} - \min_i y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \tag{15}$$

$$H_{ij} = \frac{\min_i y_{ij} - y_{ij}}{\max_i y_{ij} - \min_i y_{ij}} \tag{16}$$

The sum and power-weighted decision matrix are computed

$$D_i = \sum_{j=1}^{n} \left(W_j H_{ij}\right) \tag{17}$$

$$F_i = \sum_{j=1}^{n} \left(H_{ij}\right)^{W_j} \tag{18}$$

Determine the appraisal scores

$$Q_{ia} = \frac{D_i + F_i}{\sum_{i=1}^{m} (D_i + F_i)} \tag{19}$$

$$Q_{ib} = \frac{D_i}{\min D_i} + \frac{F_i}{\min F_i} \tag{20}$$

$$Q_{ic} = \frac{\pi(D_i) + (1-\pi)(F_i)}{\pi \max D_i + (1-\pi) \max F_i} \tag{21}$$

Determine the final value

$$Q_i = (Q_{ia} Q_{ib} Q_{ic})^{(1/3)} + \frac{1}{3}(Q_{ia} + Q_{ib} + Q_{ic}) \tag{22}$$

3. Results of ML Models

This section shows the results of the ML models on the KDD dataset.

The informational collection for the 1999 KDD Cup: This dataset includes about 4900,000 vectors from seven weeks of organization traffic, as specified by the DARPA'98 IDS assessment program. The following are the four types of replicated attacks: The 41 highlights in the KDD Cup 1999 dataset are divided into the three classes that go with it: 1) a remote-to-neighborhood (R2L) assault, 2) a client-to-root (U2R) attack, 3) a testing attack, and 4) a denial-of-service (DoS) attack. The first three are traffic, content, and establishment highlights. To eliminate necessary characteristics, a TCP/IP association is used. Traffic highlights are divided into two categories: highlights for "same host" and highlights for "same assistance." The chemical highlights raise concerns about behavior associated with information. Fig 1 shows the distribution of the attacks. Fig 2 shows the histogram of the attacks. Fig 3 shows the heatmap between the features.

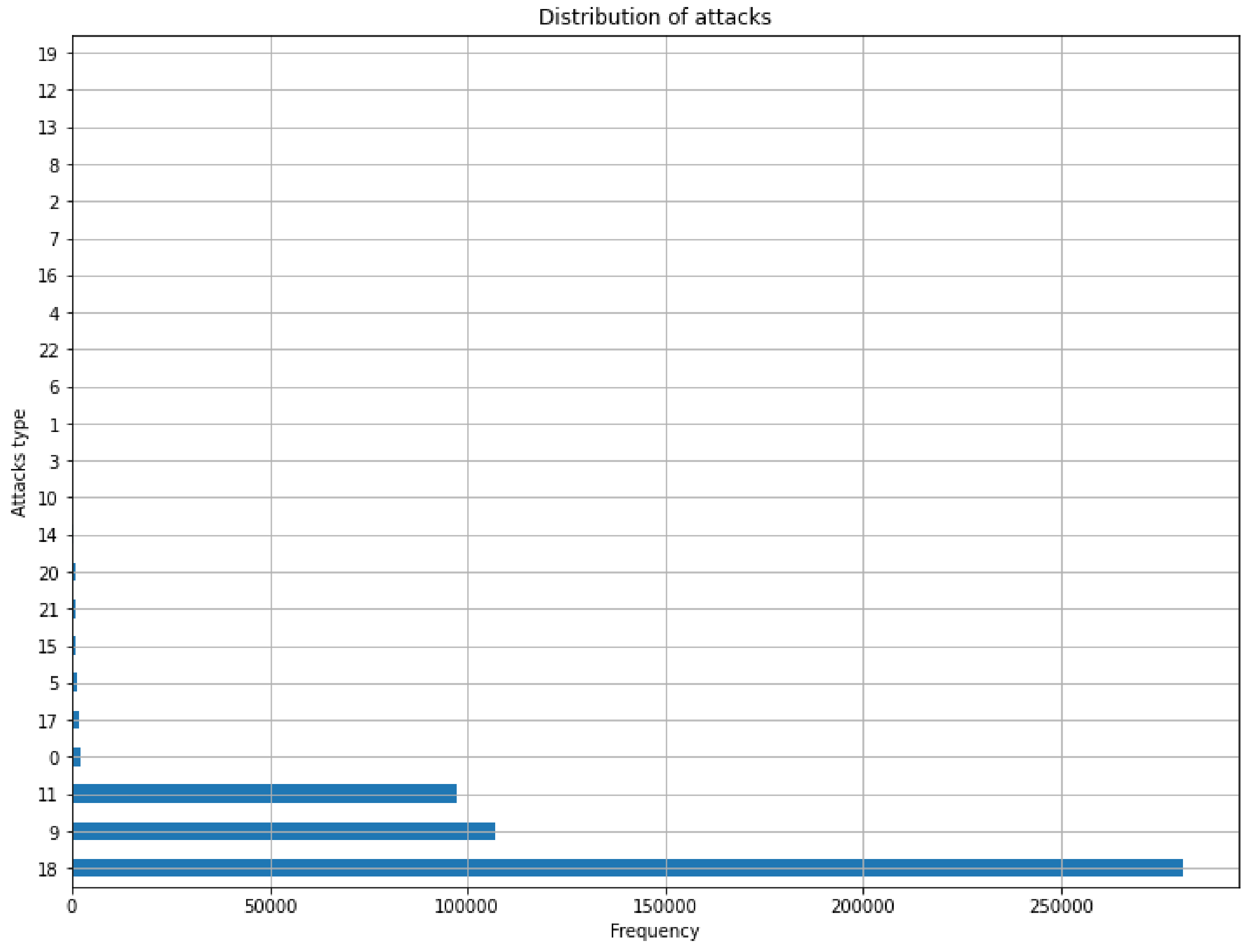

Fig 1. The distribution of the attacks.

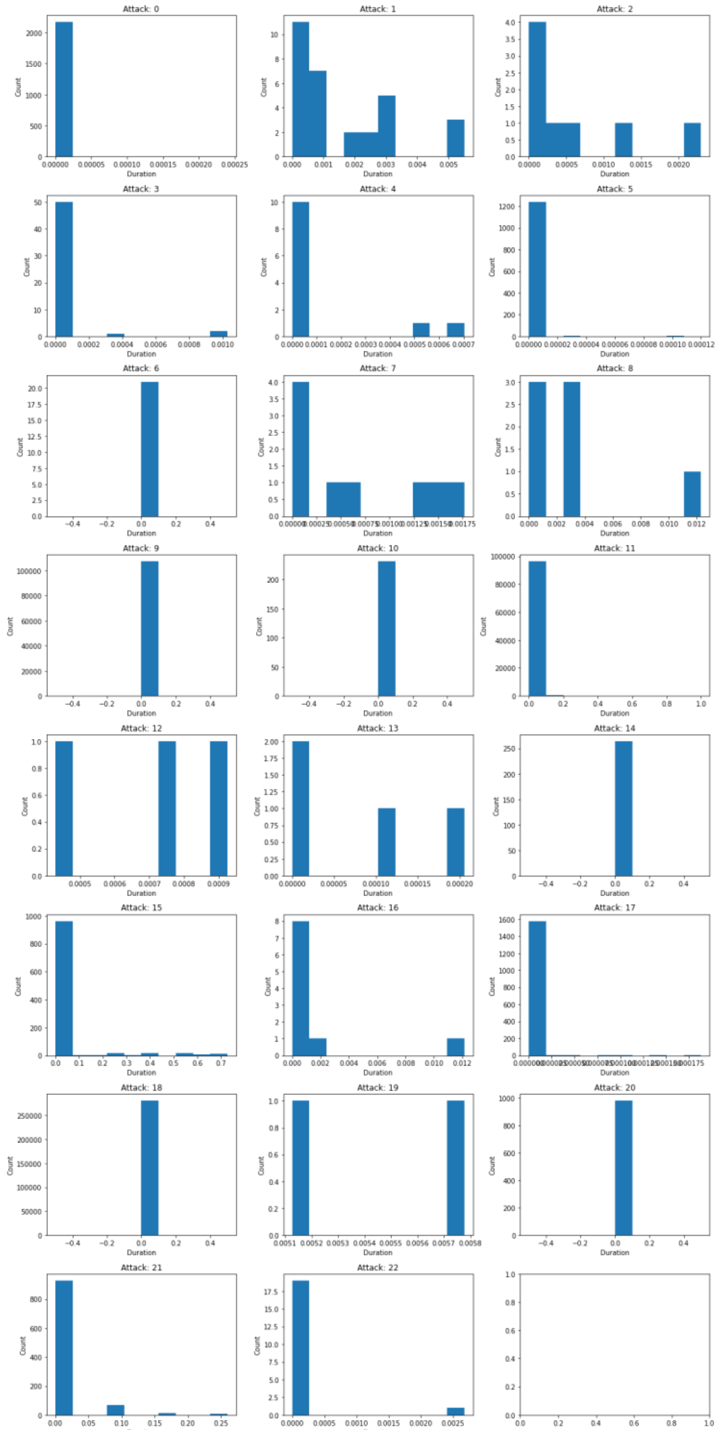

Fig 2. The histogram of the attacks.

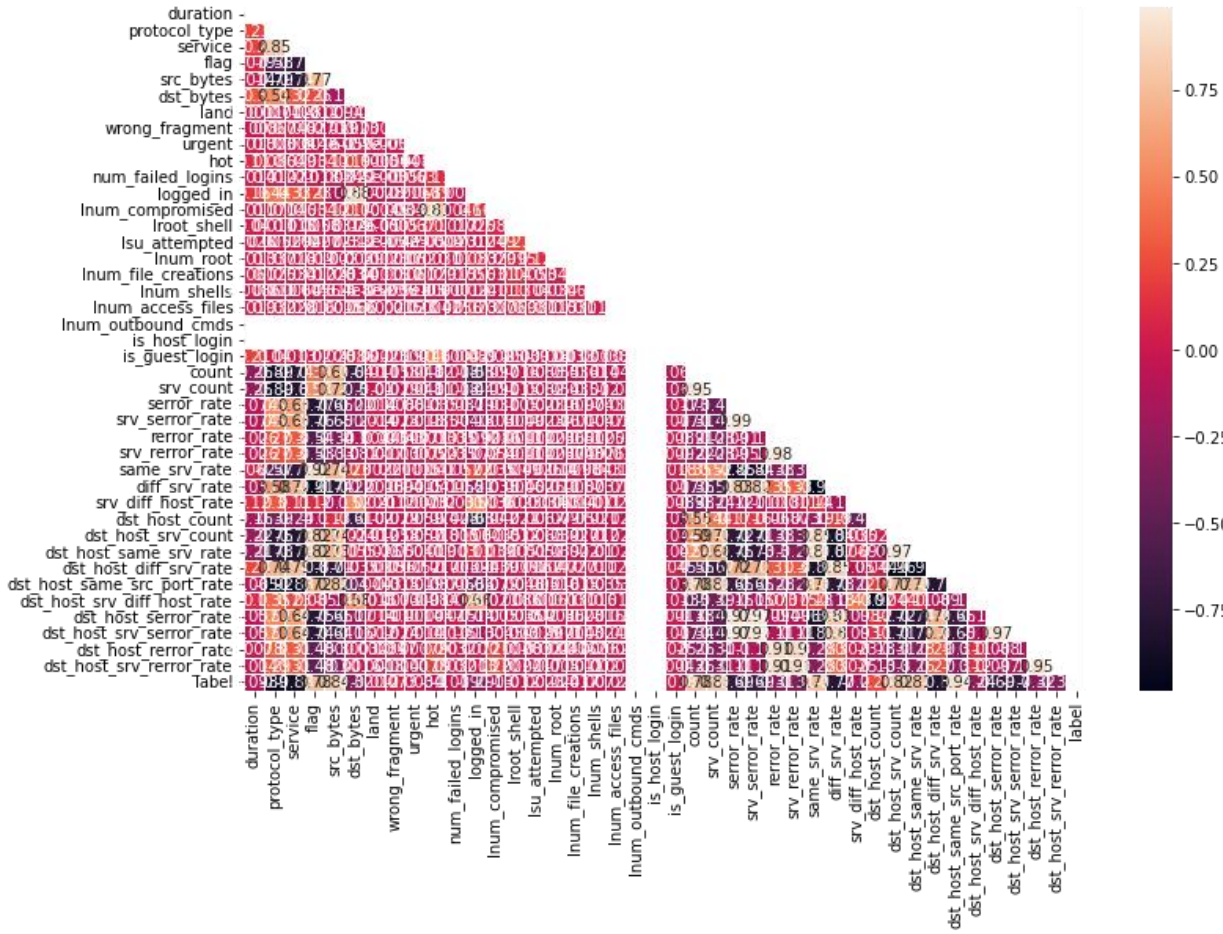

Fig 3. The heatmap of the features.

Table 1 shows the results of the ML models under different evaluation matrices. We show the k-nearest neighbor (KNN) with k=5 is the best model.

Table 1. The results of ML models.

	Accuracy	Precision	Recall	F1-score
KDCA$_1$	0.991573	0.589729	0.551429	0.561419
KDCA$_2$	0.991242	0.588684	0.548719	0.559742
KDCA$_3$	0.993192	0.594458	0.543208	0.550045
KDCA$_4$	0.992537	0.580794	0.540766	0.545454
KDCA$_5$	0.993118	0.59368	0.542076	0.549423
KDCA$_6$	0.993064	0.589177	0.538599	0.54513
KDCA$_7$	0.99305	0.623022	0.542148	0.552717
KDCA$_8$	0.993091	0.624862	0.541911	0.554386
KDCA$_9$	0.993077	0.618149	0.541357	0.552938
KDCA$_{10}$	0.993077	0.619933	0.542825	0.554313
KDCA$_{11}$	0.991573	0.589729	0.551429	0.561419

$KDCA_{12}$	0.991242	0.588684	0.548719	0.559742

4. Results of Neutrosophic with CoCoSo method

This section shows the results of the Neutrosophic model with the CoCoSo method to rank the ML models and select the best one. We use 12 ML models and 4 evaluation metrics.

Eq. (14) is used to create the decision matrix using neutrosophic numbers by three experts as shown in Tables 2-4. The decision matrices are combined into a single matrix and obtain the criteria weights as: 0.253190891, 0.246724768, 0.252853528, 0.247230813.

Table 2. The first decision matrix.

	$KDCC_1$	$KDCC_2$	$KDCC_3$	$KDCC_4$
$KDCA_1$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_2$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_3$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_4$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_5$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_6$	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_7$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_8$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_9$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{10}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{11}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{12}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]

Table 3. The second decision matrix.

	$KDCC_1$	$KDCC_2$	$KDCC_3$	$KDCC_4$
$KDCA_1$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_2$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_3$	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_4$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]

$KDCA_5$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_6$	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_7$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_8$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_9$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{10}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{11}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{12}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]

Table 4. The third decision matrix.

	$KDCC_1$	$KDCC_2$	$KDCC_3$	$KDCC_4$
$KDCA_1$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_2$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_3$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_4$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_5$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_6$	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_7$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_8$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_9$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{10}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{11}$	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]
$KDCA_{12}$	[((0.2,0.3,0.4,0.5),(0,0.1,0.2,0.3),(0,0.1,0.2,0.2)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.4,0.5,0.6,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]	[((0,0.1,0.1,0.2),(0.1,0.1,0.1,0.1),(0.6,0.7,0.8,0.9)),((0.7,0.7,0.7,0.7),(0,0.1,0.2,0.3),(0.1,0.1,0.1,0.1))]

Eqs. (15 and 16) are used to normalize the decision matrix for beneficial and non-beneficial criteria as shown in Table 5. We show the KNN with k=5 is the best model.

The sum and power-weighted decision matrix are computed using eqs. (17 and 18) as shown in Tables 6-7.

Determine the appraisal scores using eqs. (19-21)

Determine the final value using eq. (22) and rank the alternatives are shown in Fig 4.

Table 5. The normalized decision matrix.

	$KDCC_1$	$KDCC_2$	$KDCC_3$	$KDCC_4$
$KDCA_1$	0.311594	1	0.840909	0.130435
$KDCA_2$	0	0.666667	0	1
$KDCA_3$	0.956522	0.891304	0.840909	0.130435
$KDCA_4$	0.355072	0.333333	0.742424	0
$KDCA_5$	0.57971	0.623188	0.371212	0.666667
$KDCA_6$	1	0.086957	0.954545	0.268116
$KDCA_7$	0	0.869565	0.045455	0.978261
$KDCA_8$	0.934783	0.934783	1	0.311594
$KDCA_9$	0	0.043478	0.280303	0.043478
$KDCA_{10}$	0.934783	0.130435	0.606061	1
$KDCA_{11}$	0.666667	0	0.977273	0.934783
$KDCA_{12}$	0.804348	0.130435	0.136364	0.311594

Table 6. The sum weighted matrix.

	$KDCC_1$	$KDCC_2$	$KDCC_3$	$KDCC_4$
$KDCA_1$	0.078893	0.246725	0.212627	0.032247
$KDCA_2$	0	0.164483	0	0.247231
$KDCA_3$	0.242183	0.219907	0.212627	0.032247
$KDCA_4$	0.089901	0.082242	0.187725	0
$KDCA_5$	0.146777	0.153756	0.093862	0.164821
$KDCA_6$	0.253191	0.021454	0.24136	0.066287
$KDCA_7$	0	0.214543	0.011493	0.241856
$KDCA_8$	0.236678	0.230634	0.252854	0.077036
$KDCA_9$	0	0.010727	0.070876	0.010749
$KDCA_{10}$	0.236678	0.032181	0.153245	0.247231
$KDCA_{11}$	0.168794	0	0.247107	0.231107
$KDCA_{12}$	0.203654	0.032181	0.03448	0.077036

Table 7. The power-weighted matrix.

	$KDCC_1$	$KDCC_2$	$KDCC_3$	$KDCC_4$
$KDCA_1$	0.744357	1	0.957134	0.604363
$KDCA_2$	0	0.904803	0	1

$KDCA_3$	0.988808	0.972009	0.957134	0.604363
$KDCA_4$	0.769386	0.762575	0.927457	0
$KDCA_5$	0.871058	0.889872	0.778355	0.904617
$KDCA_6$	1	0.547393	0.988306	0.72221
$KDCA_7$	0	0.966105	0.457682	0.994581
$KDCA_8$	0.983069	0.983498	1	0.749548
$KDCA_9$	0	0.461347	0.724988	0.460616
$KDCA_{10}$	0.983069	0.604986	0.881066	1
$KDCA_{11}$	0.902434	0	0.994204	0.983465
$KDCA_{12}$	0.946366	0.604986	0.604234	0.749548

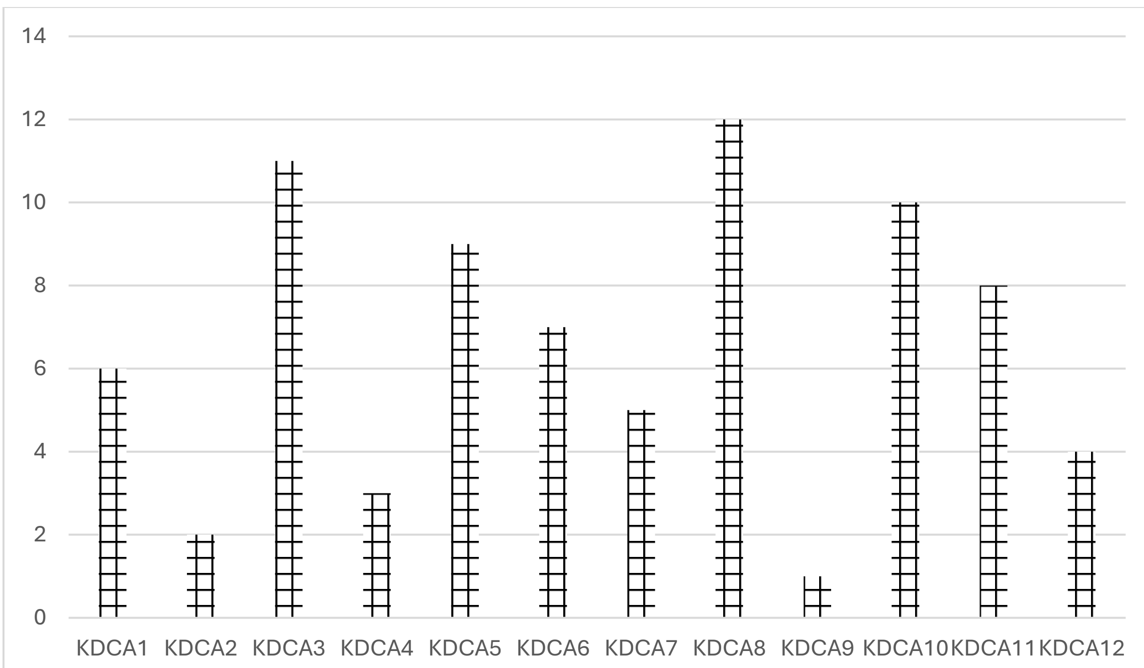

Fig 4. Rank of ML models.

5. Conclusions

This study uses ML models to propose an approach to SG energy management with cloud security analysis. The suggested approach will support smart grid frameworks. The reliability of smart grid frameworks was enhanced using real characteristics produced by the suggested specialist-based approach, and the suggested technique was accepted using the Digital Attack replay. We use the KDD dataset to evaluate ML models. We use the neutrosophic set model to select the best ML model under different evaluation matrices. We evaluated the ML models under four evaluation metrics. We used KNN with k=3 to 12. The CoCoSo method is used to rank ML models. The criteria weights are computed using the average method. The results show the KNN with k=5 is the best under different evaluation matrices.

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