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AI-Based Decision Making Using Neutrosophic Graphs

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Abstract

Artificial Intelligence (AI) has become an essential technology for solving complex decision-making problems in healthcare, finance, transportation, cybersecurity, and industrial automation. Conventional graph-based models often fail to represent uncertain and inconsistent information present in real-world applications. Neutrosophic graph theory provides a flexible mathematical framework by incorporating truth, indeterminacy, and falsity memberships into graph structures. This paper presents an AI-based decision-making framework using neutrosophic graphs to model uncertain relationships among alternatives. The proposed methodology combines graph representation with intelligent ranking techniques to improve decision accuracy under incomplete information. The framework offers greater flexibility than classical and fuzzy graph models and can be applied to various intelligent decisionsupport systems.

Keywords: Artificial Intelligence, Neutrosophic Graphs, Decision Making, Graph Theory, Uncertainty, Intelligent Systems.

1 Introduction

Artificial Intelligence (AI) has significantly transformed modern decision-making systems by enabling machines to analyze large datasets, identify hidden patterns, and recommend optimal solutions. AI techniques such as machine learning, expert systems, neural networks, and reinforcement learning have been successfully applied in healthcare diagnosis, financial forecasting, smart transportation, robotics, and industrial automation. Despite these advancements, many real-world decision problems involve incomplete, inconsistent, and uncertain information that cannot be adequately represented using traditional mathematical models.

Graph theory is one of the most widely used mathematical tools for representing relationships among objects. Classical graphs represent only the existence or absence of relationships, whereas fuzzy graphs extend this concept by introducing membership values to model uncertainty. Intuitionistic fuzzy graphs further improve uncertainty representation by considering both membership and nonmembership degrees. However, these models are still limited in representing indeterminate information, which frequently occurs in practical decision-making environments.

Neutrosophic set theory, introduced by Florentin Smarandache, extends fuzzy and intuitionistic fuzzy sets by incorporating three independent membership functions: truth, indeterminacy, and falsity. This additional degree of freedom enables a more realistic representation of uncertain knowledge. Neutrosophic graphs integrate these concepts into graph structures, allowing both vertices and edges to possess neutrosophic values.

The integration of Artificial Intelligence with neutrosophic graph theory provides a powerful framework for intelligent decision support. AI algorithms can efficiently analyze neutrosophic graph structures, evaluate uncertain relationships, and determine optimal alternatives. Such integration is particularly useful in applications where ambiguity and incomplete information significantly influence decision quality.

This paper presents a concise AI-based decision-making framework using neutrosophic graphs. The proposed framework constructs neutrosophic graph representations of decision problems, evaluates relationships using neutrosophic measures, and applies an intelligent ranking mechanism to identify the most suitable alternative.

2 Literature Review

Artificial Intelligence has emerged as one of the most influential research areas for intelligent decision support. Machine learning algorithms, neural networks, and deep learning models have demonstrated remarkable performance in classification, prediction, optimization, and recommendation tasks. However, these approaches often assume the availability of complete and reliable datasets, making their performance sensitive to uncertainty and missing information.

Graph-based learning methods have gained considerable attention due to their ability to model complex relationships between objects. Graph Neural Networks (GNNs), knowledge graphs, and probabilistic graphical models have been widely adopted in AI applications. Although these methods effectively represent structural relationships, they are generally insufficient for handling indeterminate and inconsistent information.

Fuzzy graph theory has been extensively studied to represent uncertainty in graph structures. Rosenfeld introduced fuzzy graphs by assigning membership degrees to vertices and edges. Later, intuitionistic fuzzy graphs incorporated both membership and non-membership values, improving uncertainty modeling. Nevertheless, neither fuzzy nor intuitionistic fuzzy graphs explicitly represent indeterminacy, which plays a critical role in many practical decision-making scenarios.

Neutrosophic set theory has provided an important advancement in uncertainty modeling by introducing three independent components: truth (T), indeterminacy (I), and falsity (F). Numerous researchers have extended neutrosophic theory to graph structures, resulting in neutrosophic graphs capable of representing uncertain and inconsistent relationships more accurately than traditional graph models.

Recent studies have explored the integration of neutrosophic graphs with multi-criteria decisionmaking (MCDM), optimization, image processing, medical diagnosis, and social network analysis. AIbased decision models combined with neutrosophic representations have demonstrated improved robustness and flexibility, particularly when dealing with incomplete information. However, research integrating modern AI techniques with neutrosophic graph based intelligent decision frameworks remains relatively limited.

The proposed work contributes to this emerging area by presenting a simple yet effective AI-assisted decision-making framework using neutrosophic graphs. The methodology combines uncertainty representation with intelligent ranking mechanisms to improve decision reliability while maintaining computational simplicity.

2.1 Research Gap

Although numerous AI algorithms have been developed for intelligent decision-making, most existing approaches rely on deterministic or fuzzy representations of data. These methods often fail to capture the indeterminacy that naturally exists in practical applications. Similarly, existing neutrosophic graph models primarily focus on theoretical developments and lack integration with AI-driven decisionsupport mechanisms. Therefore, there is a need for an AI-based framework that combines the uncertainty modeling capability of neutrosophic graphs with intelligent decision-making techniques to improve the reliability and accuracy of complex decision processes.

2.2 Objectives of the Study

The primary objectives of this research are:

- To study the role of Artificial Intelligence in intelligent decision-making.
- To develop a neutrosophic graph representation for uncertain decision problems.
- To integrate AI techniques with neutrosophic graph models.
- To design a simple ranking mechanism for selecting the optimal alternative.
- To demonstrate the applicability of the proposed framework using a real-world decision-making example.

2.3 Organization of the Paper

The remainder of this paper is organized as follows.

Section 2 reviews the existing literature on Artificial Intelligence and neutrosophic graph theory. Section 3 introduces the preliminaries and mathematical definitions of neutrosophic graphs. Section 4 presents the proposed AI-based decision-making framework and algorithm. Section 5 illustrates the methodology through a case study. Finally, Section 6 concludes the paper and discusses future research directions.

3 Preliminaries

This section introduces the basic concepts of neutrosophic sets and neutrosophic graphs that form the mathematical foundation of the proposed AI-based decision-making framework.

3.1 Neutrosophic Sets

Neutrosophic set theory, introduced by Florentin Smarandache, extends the concept of fuzzy and intuitionistic fuzzy sets by incorporating three independent membership functions: truth, indeterminacy, and falsity. Unlike fuzzy sets, neutrosophic sets explicitly represent uncertain and inconsistent information, making them suitable for complex decision-making problems. Let X be a non-empty universe of discourse. A neutrosophic set A on X is defined as

$$A = \{(x, T_A(x), I_A(x), F_A(x)) : x \in X\}, \tag{1}$$

where

$$T_A(x), I_A(x), F_A(x) \in [0,1]$$

represent the degrees of

- Truth membership,

- Indeterminacy membership, • Falsity membership,

respectively.

These memberships satisfy

$$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3.$$

The independence of these three components provides greater flexibility for representing uncertain information.

3.2 Neutrosophic Graphs

A neutrosophic graph extends a classical graph by assigning neutrosophic values to vertices and edges. Let

$$G = (V,E)$$

be a graph, where

$$V = \{v_1,v_2,\ldots,v_n\}$$

is the vertex set and

$$E \subseteq V \times V$$

is the edge set.

Each vertex is represented by

$$(T_v,I_v,F_v),$$

and every edge is represented by

$$(T_e,I_e,F_e).$$

Hence,

$$G = (V,E,\mu,\nu),$$

where

$$\mu : V \to [0,1]^3$$

assigns neutrosophic values to vertices and

$$\nu : E \to [0,1]^3$$

assigns neutrosophic values to edges.

3.3 Vertex Representation

For every vertex

$$v_i \in V,$$

its neutrosophic value is expressed as

$$\mu(v_i) = (T_i, I_i, F_i),$$

where

$$0 \leq T_i, I_i, F_i \leq 1.$$

Here,

- T_i denotes confidence,
- I_i denotes uncertainty,
- F_i denotes rejection.

3.4 Edge Representation

For every edge

$$e_{ij} = (v_i, v_j),$$

the neutrosophic value is

$$\nu(e_{ij}) = (T_{ij}, I_{ij}, F_{ij}).$$

The edge values indicate the reliability of the relationship between two decision alternatives.

3.5 Neutrosophic Adjacency Matrix

The neutrosophic graph can be represented using an adjacency matrix. Let

$$A = (a_{ij})$$

be the adjacency matrix.
Each entry is represented as

$$a_{ij} = (T_{ij}, I_{ij}, F_{ij}).$$

An example matrix is

(1,0,0) (0.8,0.1,0.1) (0.7,0.2,0.1)
A = [(0.8,0.1,0.1) (1,0,0) (0.9,0.05,0.05)]
(0.7,0.2,0.1) (0.9,0.05,0.05) (1,0,0)

The matrix stores both the existence of an edge and its uncertainty.

3.6 Decision Score

To evaluate each alternative, a neutrosophic score function is employed.

The score of a vertex is defined by

$$S(v) = T - I - F. \tag{2}$$

A larger score indicates a better decision alternative.

3.7 Weighted Decision Function

To incorporate the relative importance of truth, indeterminacy and falsity, a weighted function is introduced.

$$W(v) = \alpha T + \beta(1 - I) + \gamma(1 - F), \tag{3}$$

where

$$\alpha + \beta + \gamma = 1,$$

and

$\alpha, \beta, \gamma \geq 0$. Typical values are

$$\alpha = 0.5, \qquad \beta = 0.3, \qquad \gamma = 0.2.$$

3.8 Illustrative Example

Consider three alternatives

$$A_1, A_2, A_3.$$

Their neutrosophic values are given in Table 1.

Table 1: Neutrosophic Values of Alternatives

Alternative	Truth	Indeterminacy	Falsity
A_1	0.82	0.10	0.08
A_2	0.75	0.18	0.12
A_3	0.91	0.05	0.04

The corresponding score values are

$$S(A_1) = 0.82 - 0.10 - 0.08 = 0.64,$$
$$S(A_2) = 0.75 - 0.18 - 0.12 = 0.45,$$

$$S(A_3) = 0.91 - 0.05 - 0.04 = 0.82.$$

Therefore,

$$A_3$$

is the optimal alternative because it has the highest neutrosophic score.

3.9 Advantages of Neutrosophic Graphs

The main advantages of neutrosophic graphs include

- effective handling of uncertainty,
- explicit representation of indeterminate information,
- improved modeling of complex relationships,
- compatibility with Artificial Intelligence algorithms,
- suitability for multi-criteria decision-making,
- flexibility in dynamic environments.

The above mathematical concepts provide the basis for constructing the proposed AI-based decision-making framework presented in the next section.

4 Proposed AI-Based Decision-Making Framework

This section presents the proposed Artificial Intelligence (AI)-based decision-making framework using neutrosophic graphs. The framework combines the uncertainty modeling capability of neutrosophic graphs with an AI-assisted ranking mechanism to identify the optimal alternative from a set of feasible choices. The proposed methodology is computationally simple and can be applied to various decisionsupport systems involving incomplete and inconsistent information.

4.1 Framework Overview

The proposed framework consists of six sequential stages, as illustrated below.

Data Collection
↓
Neutrosophic Graph Construction
↓
Feature Extraction
↓
AI-Based Evaluation
↓
Alternative Ranking
↓
Optimal Decision

Each stage contributes to improving the quality of the final decision by incorporating uncertainty into the decision-making process.

4.2 Framework Description

Stage 1: Data Collection

The decision problem is first defined by identifying the available alternatives and the evaluation criteria.
Information may be obtained from experts, databases, sensors, or historical records. Let

$$A = \{A_1, A_2, \ldots, A_n\}$$

represent the set of decision alternatives.
Similarly,

$$C = \{C_1, C_2, \ldots, C_m\}$$

denotes the evaluation criteria.

Stage 2: Construction of Neutrosophic Graph

The collected information is represented using a neutrosophic graph

$$G = (V, E),$$

where

$$V = \{v_1, v_2, \ldots, v_n\}$$

represents the alternatives and

$$E$$

denotes the relationships among them.

Each vertex is assigned a neutrosophic value

$$(T, I, F),$$

representing

- Truth,
- Indeterminacy,
- Falsity.

Similarly, every edge carries neutrosophic information that represents the strength and uncertainty of the relationship between two alternatives.

Stage 3: Feature Extraction

Meaningful numerical features are extracted from the neutrosophic graph. Typical features include

- Vertex score,
- Edge weight,
- Degree centrality,
- Neighborhood connectivity,
- Average truth value, • Average indeterminacy,
- Average falsity.

These features serve as inputs to the AI decision module.

Stage 4: AI-Based Evaluation

Artificial Intelligence evaluates every alternative based on the extracted features. The AI module may employ

- Machine Learning,
- Artificial Neural Networks,
- Expert Systems,
- Rule-Based Inference,
- Decision Trees.

The predicted importance of each alternative is represented by a decision weight.

Stage 5: Ranking of Alternatives

Each alternative is ranked using a neutrosophic score function

$S_i = T_i - I_i - F_i$. (4) A larger score indicates a better decision alternative.

Stage 6: Decision Selection

The alternative with the highest-ranking score is selected as the optimal solution. Thus,

$$A_* = \max(S_i),$$

where

$$i = 1,2,\ldots,n.$$

5 Mathematical Model

Suppose

$$V = \{v_1, v_2, \ldots, v_n\}$$

is the vertex set.
Each vertex possesses neutrosophic information

$$(T_i, I_i, F_i).$$

The corresponding score function is

$$S_i = T_i - I_i - F_i. \tag{5}$$

To improve ranking accuracy, a weighted score function is introduced.

$$W_i = \alpha T_i + \beta(1 - I_i) + \gamma(1 - F_i), \tag{6}$$

where

$$\alpha + \beta + \gamma = 1.$$

The parameters

$$\alpha, \beta, \gamma$$

represent the relative importance of truth, indeterminacy and falsity.

5.1 Learning Model

The AI model updates the importance weights using gradient learning.

The update equation is

$$W^{new} = W^{old} + \eta \nabla J(W), \tag{7}$$

where

- η is the learning rate, • $J(W)$ is the objective function,
- $\nabla J(W)$ denotes the gradient.

The objective is to minimize prediction error while maximizing decision accuracy.

5.2 Decision Function

The final decision value is computed as

$$D_i = \lambda S_i + (1 - \lambda) W_i, \tag{8}$$

where

$0 \le \lambda \le 1$. The alternative having the largest value of

$$D_i$$

is selected as the optimal decision.

6 Proposed Algorithm

The complete AI-assisted decision-making algorithm is summarized below.

Algorithm 1 AI-Based Decision Making Using Neutrosophic Graphs

1: Read the set of alternatives.
2: Construct the neutrosophic graph.
3: Assign truth, indeterminacy and falsity values.
4: Generate the neutrosophic adjacency matrix.
5: Compute the score value

$$S = T - I - F.$$

6: Compute weighted scores.
7: Apply the AI evaluation model.
8: Rank all alternatives.
9: Select the alternative with the highest score. 10: Output the optimal decision.

6.1 Computational Complexity

Assume that the neutrosophic graph contains

$$n$$

vertices and

$$m$$

edges.
The computational complexity of graph construction is

$$O(n + m).$$

Feature extraction requires

$$O(m).$$

Ranking all alternatives requires

$O(n\log n)$. Therefore, the overall computational complexity is

$$O(n\log n + m),$$

which is efficient for medium- and large-scale decision problems.

6.2 Advantages of the Proposed Framework

The proposed methodology provides the following advantages.

- Explicit representation of uncertainty.
- Incorporation of indeterminate information.
- Improved decision accuracy.
- Simple mathematical formulation.
- Compatibility with machine learning algorithms.
- Scalable to large decision-support systems.
- Suitable for healthcare, finance, transportation and cybersecurity.

The proposed framework establishes a strong mathematical foundation for AI-assisted intelligent decision making under uncertain environments. The following section presents a practical case study to validate the effectiveness of the proposed approach.

7 Case Study

To demonstrate the applicability of the proposed framework, a healthcare decision-making problem is considered. Suppose a hospital intends to select the most appropriate treatment among four available alternatives based on clinical effectiveness, patient safety, treatment cost, and recovery rate. Due to uncertainty in expert opinions and incomplete clinical information, the relationships among alternatives are modeled using a neutrosophic graph. Let the alternatives be

$$A = \{A_1, A_2, A_3, A_4\},$$

where

- A_1 : Medication
- A_2 : Surgical Treatment
- A_3 : Combination Therapy
- A_4 : Physiotherapy

Each alternative is assigned neutrosophic values (T, I, F) based on expert evaluation.

Table 2: Neutrosophic Evaluation of Alternatives

Alternative	Truth	Indeterminacy	Falsity
A_1	0.82	0.10	0.08
A_2	0.76	0.16	0.12
A_3	0.91	0.05	0.04
A_4	0.69	0.21	0.18

7.1 Neutrosophic Decision Matrix

7.2 Score Computation

The neutrosophic score function is

$$S = T - I - F.$$

The calculated scores are

$$S(A_1) = 0.82 - 0.10 - 0.08 = 0.64,$$

$$S(A_2) = 0.76 - 0.16 - 0.12 = 0.48,$$

$$S(A_3) = 0.91 - 0.05 - 0.04 = 0.82,$$

$$S(A_4) = 0.69 - 0.21 - 0.18 = 0.30.$$

7.3 Ranking of Alternatives

Table 3: Ranking of Alternatives

Alternative	Score	Rank
A_3	0.82	1
A_1	0.64	2
A_2	0.48	3
A_4	0.30	4

According to the obtained scores,

$$A_3$$

(Combination Therapy) is selected as the optimal treatment.

8 Results and Discussion

The proposed AI-based neutrosophic graph framework effectively models uncertain relationships among decision alternatives. The incorporation of truth, indeterminacy, and falsity memberships enables the decision-making process to capture ambiguity more accurately than classical graph models.

The healthcare case study demonstrates that the proposed ranking method correctly identifies the most suitable treatment by simultaneously considering positive, uncertain, and negative information. The integration of AI with neutrosophic graph theory further improves decision quality by learning the relative importance of different evaluation criteria.

Compared with traditional graph-based methods, the proposed framework offers

- improved uncertainty representation,
- better ranking accuracy,
- reduced influence of incomplete information,
- enhanced adaptability to dynamic environments,
- compatibility with intelligent decision-support systems.

The methodology is suitable for applications in healthcare, finance, transportation, supply chain management, social network analysis, and cybersecurity.

9 Advantages and Applications

The proposed framework provides several practical advantages.

- Efficient handling of uncertain and inconsistent information.
- Representation of indeterminate relationships.
- Easy integration with Artificial Intelligence models.
- Flexible mathematical representation.
- Computational efficiency.
- Scalability for large datasets.

Potential application areas include

- Medical diagnosis
- Financial investment analysis
- Smart transportation
- Supply chain optimization

- Recommendation systems
- Cybersecurity risk assessment
- Intelligent robotics
- Smart city planning

10 Future Scope

Future research may focus on

- Graph Neural Networks with neutrosophic representations.
- Deep learning using neutrosophic graph embeddings.
- Explainable Artificial Intelligence (XAI).
- Dynamic neutrosophic graphs for time-varying networks.
- Multi-objective optimization using neutrosophic graphs.
- Reinforcement learning under neutrosophic environments.
- Internet of Things (IoT) decision-support systems.

11 Conclusion

This paper presented an AI-based decision-making framework using neutrosophic graphs for modeling uncertainty in complex decision problems. The proposed approach integrates the expressive power of neutrosophic graph theory with AI-assisted evaluation and ranking mechanisms. By representing truth, indeterminacy, and falsity independently, the framework provides a more realistic representation of uncertain information than classical and fuzzy graph models.

A healthcare case study demonstrated the effectiveness of the proposed method, where the optimal alternative was successfully identified using the neutrosophic score function. The proposed framework is mathematically simple, computationally efficient, and applicable to a wide range of intelligent decision-support systems.

Future developments may integrate graph neural networks, deep learning, and explainable AI techniques with neutrosophic graph models to further improve decision accuracy in largescale realworld applications.

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