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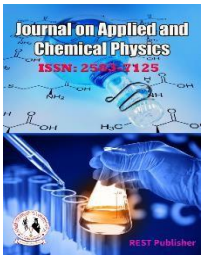

Neutrosophic MCDM and Grey Relational Approaches for Glioblastoma and Brain Cancer Metastasis Analysis

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Abstract: *This study explores the use of methods of Multi-Criteria Decision Making (MCDM), particularly Neutrosophic Grey Relational Analysis (NGRA), in assessing the glioblastoma metastasis. The study seeks to analyze the different factors that facilitate glioblastoma metastasis, and develop a systematic way of prioritizing the least significant factors that influence the progression of the disease. The outcome of this analysis can help develop appropriate strategies to manage the condition and improve the prognosis of patients with this form of brain cancer, which is highly aggressive.*

Keywords: *MCDM Method, Brain Cancer Metastasis, Glioblastoma, Grey Relational Analysis, Neutrosophic Grey Relational Analysis.*

1. INTRODUCTION

The earliest known reference relating to multiple criteria decision making can be traced to Benjamin Franklin (1706-1790) who allegedly had a simple paper system for decoding important issues. Brain cancer is also known brain tumor, is an abnormal growth of cells in brain. There is more than one distinct type of brain tumor each with its own spectrum of presentational treatment and outcomes. More than any other cancer, brain tumor can have lasting and altering physical cognitive and psychological impacts on a patient's life. There are many researchers are undertaken by the scientists but there is no improvement in survival rate of patients who are affected by brain cancer compared to other type of cancer diseases. Brain tumors are usually slow growing and less likely to spread and their cells look similar to normal cells. The metastatic spread of solid tumors is responsible directly or indirectly for most cancer related deaths [10].

Brain tumors, both primary metastatic represent a significant medical challenge due to their complex nature, unpredictable progression and high mentality note [10]. With the advancement of diagnostic and therapeutic techniques, there is an increasing need for precise assessment and management strategies. One approach gaining attention in medical research for analyzing such complex conditions in the use of Multi Criteria Decision Making (MCDM) methods [1, 11].

MCDM method facilitate decision-making by evaluating multiple conflicting criteria, making them suitable for handling the various aspects of brain cancer prognosis and treatment. In recent years, Grey Relational Analysis (GRA) and Grey Relational Ranking (GRR) have emerged robust tools within MCDM frameworks [1,12,13]. These techniques excel in managing uncertainty and incomplete information, which are common issues in medical data analysis. The grey system theory, underpinning GRA, allows for enhanced comparison of alternatives even with limited or uncertain data. This capability is particularly advantageous in brain cancer research, where patient's data after contain missing values or irregularities due to variability in diagnostic measures and disease progression.

This survey paper reviews the current research on brain tumor analysis and diagnosis using MCDM methods with a focus on GRA and GRR applications. By synthesizing the latest advancements and applications of these methods in brain cancer research, we aim to provide insights into how they contribute to more accurate diagnosis, treatment selection and prognostic predictions. The finding could not only support clinical decision-making but also open new pathways for handling complex medical data in oncology research. Neutrosophic sets (Smarandache 1995) contains triple having true, false and indeterminacy membership values that can be characterized independently. The neutrosophic set is a powerful general formal framework which generalizes the concept of the classic set

[20]. A neutrosophic set has three components: truth membership (T), indeterminacy membership(I), falsity membership(F) [9,20,19]. Smarandache (1995) defined the notion of neutrosophic sets, which is a generalized of Zadeh's fuzzy set and Atanassov's intuitionistic fuzzy set [19]. Numerous studies have linked increased transcription to the development of tumours in breast, pancreatic and brain cancer cases [2]. Over the past few decades, two key applications such as image segmentation and fusion have become much clearer and they are significant in the field of image processing and computer vision [3]. Massive investigative study challenges in computer vision and image analysis have emerged during this technological era [9].

2. CRITERIA DEVELOPMENT

Brain cancer metastasis is a leading cause of mortality, making early detection crucial for tracking and predicting disease progression. Modern technologies, such as circulating tumor cell analysis, enable the early identification of metastatic stages in brain tumor patients. Magnetic Resonance Imaging (MRI) remains a cornerstone in diagnosing brain cancer metastasis. During an MRI, a contrast agent is injected into a vein to enhance imaging. Specialized MRI techniques, including functional MRI, perfusion MRI, and magnetic resonance spectroscopy, assist in tumor evaluation and treatment planning.

Current diagnostic methods also include assessments of the metastatic cascade, clinical indicators of organ spread, biopsies, cerebrospinal fluid analysis, blood tests, liquid biopsy radiomics, and serum tumor markers. Genetic markers such as IDH1/2 mutations, TERT promoter mutations, TP53 mutations, and MGMT promoter methylation are critical for prognosis and treatment monitoring.

Brain cancer cells can spread through various pathways: local invasion, cranial nerve involvement, hematogenous spread via blood vessels, and lymphatic dissemination through cerebrospinal fluid pathways. This comprehensive approach aids in understanding the complex mechanisms of metastasis and improving patient outcomes.

TABLE 1. Some routes for carrying the cancer cell to specific organ

S.NO	Organs	Routes
1.	Lungs	Hematogenous spread
2.	Liver	Hematogenous spread
3.	Bone	Hematogenous spread
4.	Lymphnodes	Lymphetic spread (csf) pathway
5.	Kidney	Blood stream
6.	Pancreas	Lymphetic spread (csf) pathway

Patients commonly experience multiple metastasis. The most prevalent brain cancers vary depending on age, location and other factors. Here are some of the most common brain cancers show in fig 1.

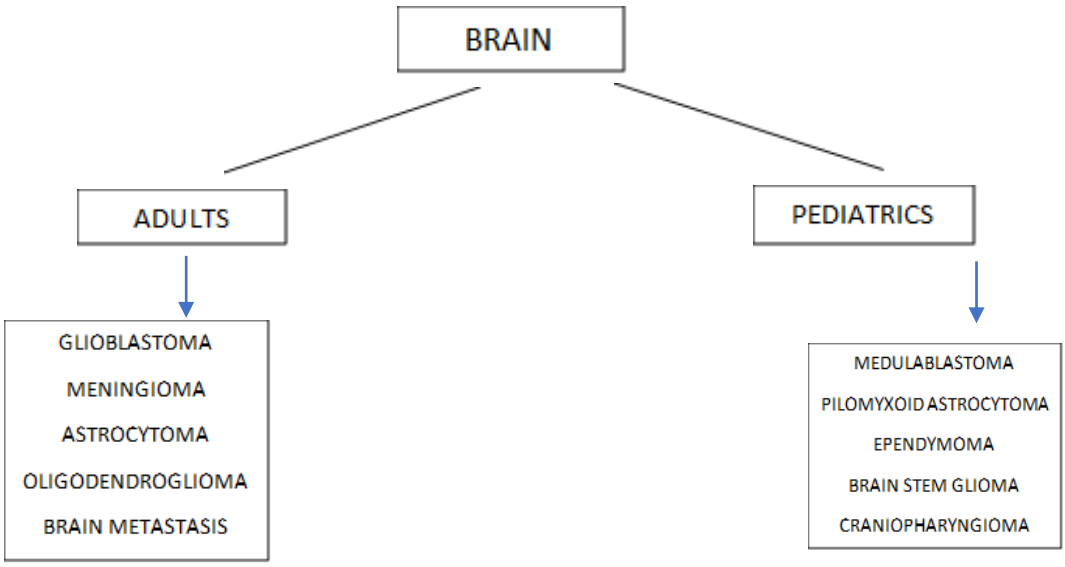

FIGURE 1.

3. PROPOSED METHOD

We will utilize the Grey Relational Analysis technique as a ranking method based on brain cancer criteria. This approach involves several steps, including defining the criteria and alternatives, normalizing the data, determining the deviation sequence, calculating the Grey Relational Grade, and ultimately establishing the ranking.

The Grey Relational Coefficient (GRC) is calculated between the target sequence and each comparison sequence to assess their relationship. This process helps determine the optimal target order among the comparison sequences based on their degree of similarity with the ideal target. The best alternative is the one with the highest Grey Relational Grade, signifying the strongest relationship.

To address Multi-Criteria Decision-Making (MCDM) challenges, we propose an enhanced Grey Relational Analysis (GRA) method. This approach incorporates linguistic variables and interval values to represent both quantitative criteria and weights when precise values are unavailable. Optimization models are employed to determine criterion weights, expanding the conventional GRA framework. In this extended method, a comparative sequence derived from an interval-valued triangular fuzzy estimate is used to identify the preferred option.

Summarizing the process, the enhanced GRA method effectively handles MCDM problems with interval-valued criteria and unknown weights. As an example, this method could be applied in selecting a computer analysis engineer for a software corporation by analyzing numerical data for compatibility.

Widely used in Asia and globally, GRA is a powerful evaluation model that assesses the degree of similarity or divergence between sequences. By analyzing factors affecting systems, GRA identifies relationships between series and reference sequences using the Grey Relational Coefficient (GRC). This makes it a robust tool for data analysis, particularly in complex decision-making scenarios.

4. PRELIMINARIES

4.1. Grey Relational Analysis

Grey Relational Analysis is a mathematical technique used to evaluate the relationships between multiple sequences or alternatives, offering a quantitative measure of their similarity or divergence.

GRA Theory is

$$\gamma_{ij}= \frac{\Delta \min + \varepsilon \Delta max}{\Delta_i(j) + \varepsilon \Delta max}$$

Here γ_{ij} is the j^{th} value in Δ_i difference data series and ε is called distinguishing coefficient = 0.5.

4.2. Normalized Data

Normalization is the process of transforming data to ensure all variables are on a consistent scale, enhancing model interpretability and preventing any single feature from dominating. Normalized data typically fall within a range of 0 to 1.

$$X_i{}^*(k) = 1 - \frac{|x_i(k) - x_i \min(k)|}{x_i \max(k) - x_i \min(k)}$$

where $X_i{}^*(k)$ is Normalized value; $x_i(k)$ is original value; $x_i \max(k)$ is maximum value in the dataset; $x_i \min(k)$ is minimum value in the dataset.

4.3. Deviation Sequence

A deviation sequence represents the absolute differences between corresponding elements of two or more sequences.

$$\Delta_{(k)}= |x^*{}_{max}(k) - x_i{}^*(k)|$$

where $\Delta_{(k)}$ is deviation sequence; $x^*{}_{max}(k)$ is reference sequence; $x_i{}^*(k)$ is comparative sequence; | is absolute value operator.

4.4. Grey Relational Coefficient

GRC measures the similarity between two sequences by considering the deviation sequence and the distinguishing coefficient.

$$\varepsilon(k) = \frac{\Delta min + \varepsilon \Delta max}{\Delta_i(k) + \Delta min}$$

where $\varepsilon(k)$ is Grey relational coefficient; Δmin is minimum absolute difference; Δmax is maximum absolute difference; ε is distinguishing coefficient; $\Delta_i(k)$ is absolute difference.

4.5. Neutrosophic set

The following is a definition of Neutrosophic Set A on X:

$$\boldsymbol{A} = \{< \boldsymbol{x}, \boldsymbol{T_A}(\boldsymbol{x}), \boldsymbol{I_A}(\boldsymbol{x}), \boldsymbol{F_A}(\boldsymbol{x}) >, \boldsymbol{x} \in \boldsymbol{X}\}$$

where $\boldsymbol{T_A},\ \boldsymbol{I_A},\ \boldsymbol{F_A} : \boldsymbol{U} \rightarrow [\boldsymbol{0}, \boldsymbol{1}]$ and $\boldsymbol{0} \leq \boldsymbol{T_A}(\boldsymbol{x}) + \boldsymbol{I_A}(\boldsymbol{x}) + \boldsymbol{F_A}(\boldsymbol{x}) \leq \boldsymbol{3}$

Here, $\boldsymbol{T_A}(\boldsymbol{x})$ is the degree of membership, $\boldsymbol{I_A}(\boldsymbol{x})$is the degree of inderminancy and $\boldsymbol{F_A}(\boldsymbol{x})$ is the degree of non-membership. Here, $\boldsymbol{T_A}(\boldsymbol{x})$ and $\boldsymbol{F_A}(\boldsymbol{x})$ are dependent neutrosophic elements and $\boldsymbol{I_A}(\boldsymbol{x})$ is an independent neutrosophic element.

5. GLIOBLASTOMA

Glioblastoma (GBM) is the most common and aggressive form of brain cancer. It develops when DNA mutations in the brain or spinal cord cause cells to grow and multiply uncontrollably, forming a tumor. GBM grows rapidly and can invade and destroy healthy tissue. It originates from astrocytes, the cells that support nerve cells in the brain. Glioblastoma can occur at any age, with an incidence ranging from 3 to 21 per 1,000,000 people. The median age of diagnosis is 64, and it is more common in men than in women.

The prognosis is poor, with approximately 40% of patients surviving the first-year post-diagnosis and only 17% surviving into the second year. Glioblastoma is rare, affecting about 3% of people annually. It is classified as a grade 4 glioma, the most aggressive type of brain tumor, arising from glial cells. Tumor grading, which ranges from 1 to 4, indicates the tumor's likelihood to grow and spread. Grade 4 gliomas, such as glioblastoma, are the most aggressive and serious, making them a particularly challenging form of cancer to treat.

6. SINGLE VALUED MCDM STRATEGY USING GREY RELATIONAL ANALYSIS

TABLE 2. Evaluation parameters criteria for segmental attractiveness.

$C1$	Lungs
$C2$	Liver
$C3$	Bone
$C4$	Eyes
$C5$	Kidney
$C6$	Pancreas
$C7$	Adrenal gland
$C8$	Pleura
$C9$	Skin
$C10$	Gastriointestinal

Table 2 The several evaluation parameters in lungs, liver, bone, adrenal gland, eyes, kidney, pancreas, pleura, skin, gastrointestinal.

TABLE 3. Alternative parameters

$A1$	Ependymoma (EPN)
$A2$	Pineal Tumour(PT)
$A3$	Medulloblastoma(MDB)
$A4$	Glioblastoma(GBM)
$A5$	Meningioma(MNG)

Table 3 shows several alternative parameters are Glioblastoma, Medulloblastoma, Pineal tumour, Meningioma, Ependymoma

TABLE 4. Data Set

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
$A1$	91.36	83.31	52.78	60.75	52.63	22.61	31.47	20.22	47.76	38.88
$A2$	89.52	73.37	63.31	71.61	70.96	25.56	54.32	27.53	27.23	34.76
$A3$	72.64	66.34	72.89	85.32	49.34	39.11	29.19	47.60	36.75	28.06
$A4$	79.83	69.51	90.26	45.62	44.28	45.22	37.00	41.77	53.78	40.00
$A5$	57.88	46.57	85.50	50.48	37.41	68.91	23.97	45.72	30.59	59.06

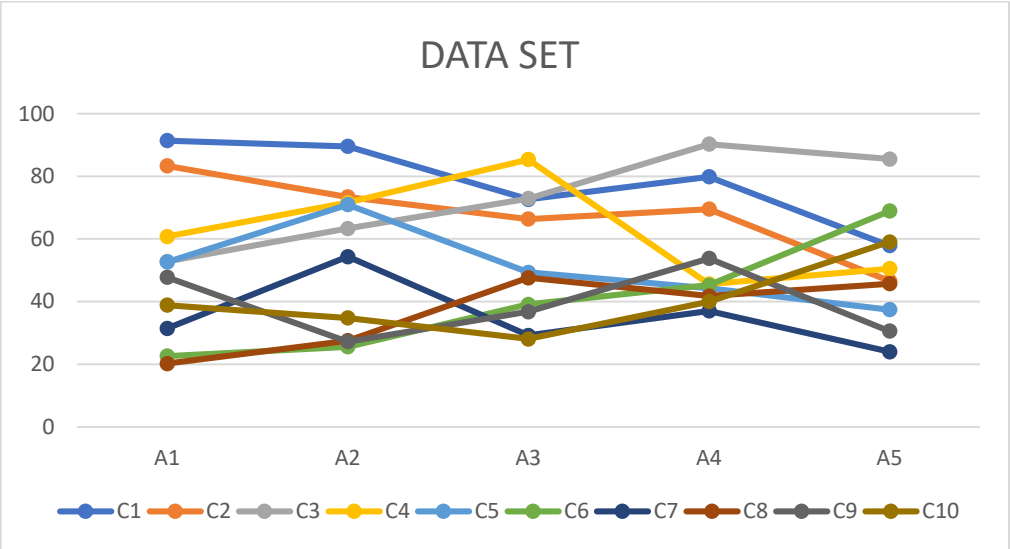

FIGURE 2.

The Normalized data is given by

$$X_i^*(k) = 1 - \frac{x_i(k) - x_i \min(k)}{x_i \max(k) - x_i \min(k)}$$

TABLE 5.

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
$A1$	0.0000	0.0000	1.0000	0.6188	0.5463	1.0000	0.7528	1.0000	0.2267	0.6509
$A2$	0.0549	0.2705	0.7190	0.3453	0.0000	0.9449	0.0000	0.7330	1.0000	0.7838S
$A3$	0.5591	0.4619	0.4634	0.0000	0.6444	0.6436	0.8280	0.0000	0.6414	1.0000
$A4$	0.3443	0.3756	0.0000	1.0000	0.7952	0.4900	0.5706	0.2129	0.0000	0.6148
$A5$	1.0000	1.0000	0.1270	0.8775	1.0000	0.0000	1.0000	0.0686	0.8734	0.0000

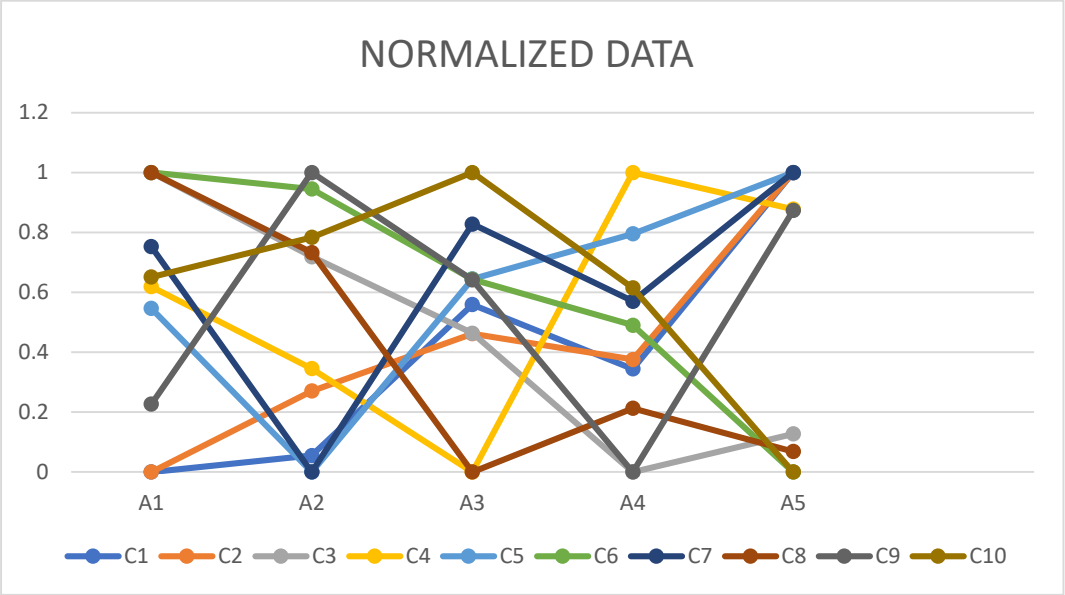

FIGURE 3. Normalized Data

Table 4 shows the normalized data for non-specific alternative parameter. The values are derived using the normalized data formula and the value are in the above tabular column

TABLE 6. Deviation Sequence

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
$A1$	1.0000	1.0000	0.0000	0.3812	0.4537	0.0000	0.2472	0.0000	0.7733	0.3491
$A2$	0.9451	0.7295	0.2810	0.6547	1.0000	0.0551	1.0000	0.2670	0.0000	0.2162
$A3$	0.4409	0.5381	0.5366	1.0000	0.3556	0.3564	0.1720	1.0000	0.3586	0.0000
$A4$	0.6557	0.6244	1.0000	0.0000	0.5100	0.5100	0.4294	0.7871	1.0000	0.3852
$A5$	0.0000	0.0000	0.8730	0.1225	1.0000	1.0000	0.0000	0.4314	0.1266	1.0000

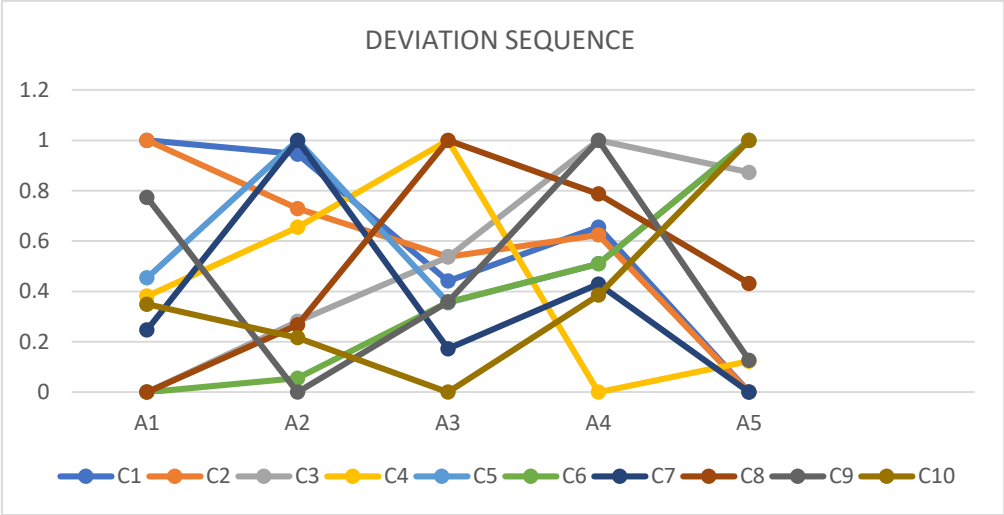

FIGURE 4.

Table 5 shows the deviation sequence value from the normalized data using formula

TABLE 7. Grey Relation Coefficient

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
$A1$	0.3333	0.3333	1.0000	0.5674	0.5243	1.0000	0.6692	1.0000	0.3927	0.5889
$A2$	0.3459	0.4067	0.6402	0.4330	0.3333	0.9007	0.3333	0.6519	1.0000	0.6981
$A3$	0.5314	0.4816	0.4823	0.3333	0.5844	0.5838	0.7440	0.3333	0.5823	1.0000
$A4$	0.4326	0.4447	0.3333	1.0000	0.7094	0.4950	0.5379	0.3885	0.3333	0.5648
$A5$	1.0000	1.0000	0.3641	0.8032	1.0000	0.3333	1.0000	0.3493	0.7979	0.3333

Table 6 is given for a grey relation coefficient

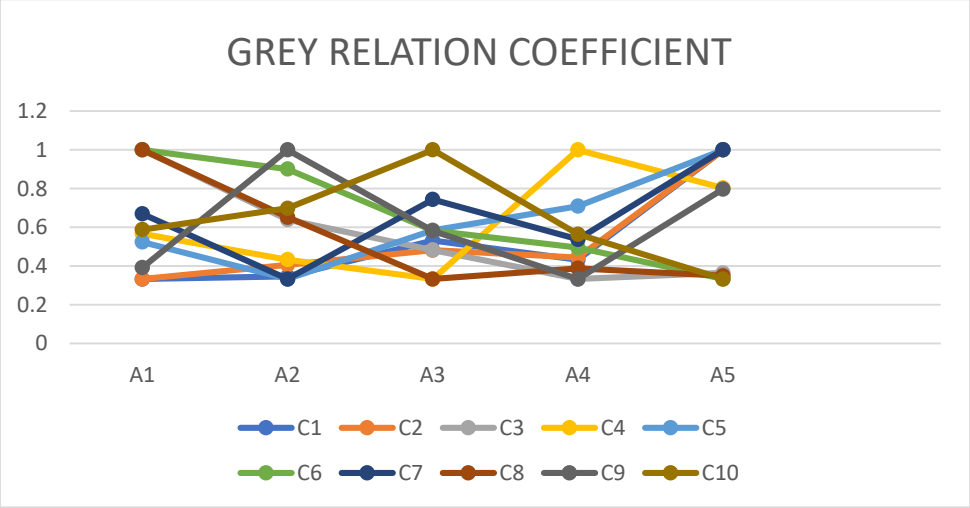

FIGURE 5.

The Grey Relational Coefficient is given by

$$\xi_i(k) = \frac{\Delta \min + \xi \Delta max}{\Delta_{ij}(k) + \xi \Delta max}$$

(A zeta value is constant and the values of 0.5).

TABLE 8. Grey Relational Analysis

A1	0.6409
A2	0.5743
A3	0.5656
A4	0.5239
A5	0.6981

TABLE 9. Ranking

$A1$	Ependymoma (EPN)	2
$A2$	Pineal Tumour(PT)	3
$A3$	Medulloblastoma(MDB)	4
$A4$	Glioblastoma(GBM)	5
$A5$	Meningioma(MNG)	1

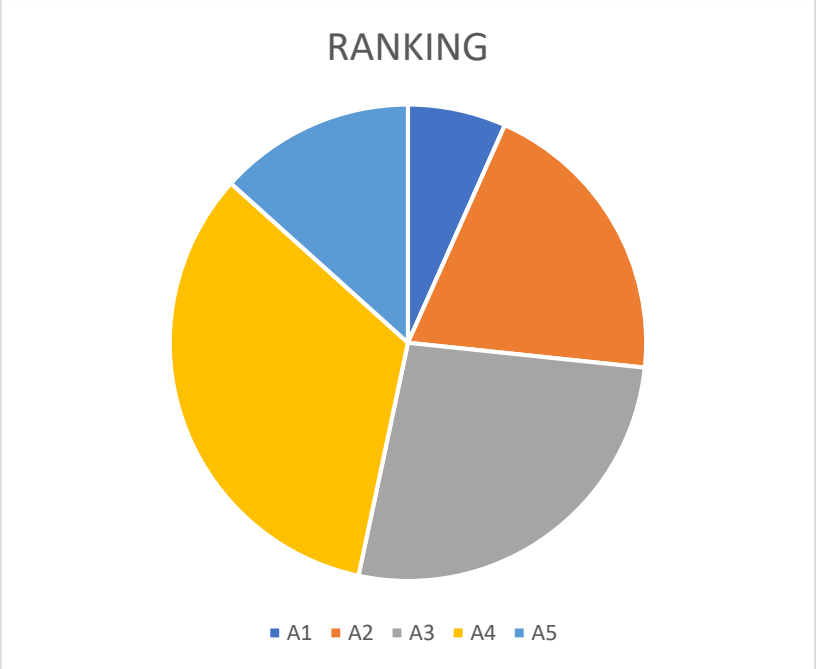

FIGURE 6.

The above table shows the rank. Here Ependymoma (EPN) is first ranking and also a low affect disease. Glioblastoma (GBM) is a last ranking disease and it is high affect disease.

7. SINGLE VALUED MCDM STRATEGY USING GREY NEUTROSOPHIC RELATIONAL ANALYSIS

Grey Neutrosophic Relational Analysis (GNRA) is a mathematical framework that integrates grey systems, neutrosophic sets and relational analysis to model and analyze complex systems with uncertain and imprecise information. By combining the strengths of grey systems in handling uncertain parameters and neutrosophic sets in representing indeterminate and inconsistent information, GNRA provides a powerful tool for identifying patterns, trends, and correlations in finance, management, and risk analysis. complex systems, ultimately supporting informed decision-making in fields such as economics,

TABLE 10. Neutrosophic Data Set

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.8,0.1,0.1) (0.2,0.8,0)	(0.2,0.1,0.7) (0.6,0.3,0.1)	(0.3,0.6,0.1) (0.4,0.3,0.3)	(0.9,0,0.1) (0.7,0.3,0)	(0.4,0.1,0.4) (0,0,1)	(0.3,0.3,0.4) (1,0,0)	(0.2,0.2,0.6) (0.7,0.3,0)	(0.1,0.5,0) (0,1,0)	(1,0,0) (0.7,0.2,0.1)	(0.2,0.3,0.5) (0.5,0.2,0.3)
A2	(0.2,0.6,0.2) (0.1,0.1,0.8)	(0.2,0.2,0.6) (1,0,0)	(0.2,0.6,0.2) (0.4,0.4,0.2)	(0.3,0.1,0.6) (0.6,0.1,0.3)	(1,0,0) (0.9,0.1,0)	(0.1,0.3,0.6) (0,0,1)	(0.1,0.2,0.7) (0.7,0.2,0.1)	(0.3,0.6,0.1) (0.2,0.2,0.2)	(0.7,0.2,0.1) (0.1,0.4,0.5)	(0.6,0.1,0.3) (0.5,0,0.5)
A3	(0.1,0.7,0.4) (0.3,0.2,0.5)	(0.5,0.5,0) (0,0.1,0.4)	(0.1,0.3,0.6) (0,0.1,0.7)	(0,0,1) (0.1,0.6,0.9)	(0.7,0.5,0.1) (0.1,0.6,0.3)	(0.2,0.4,0.4) (0.7,0.2,0.1)	(0.5,0.5,0) (0,0.1,0.6)	(0.1,0.7,0.3) (0.7,0.1,0.2)	(0.2,0.6,0.2) (0.1,0.3,0.6)	(0.6,0.2,0.2) (0.4,0,0.6)
A4	(0.1,0.7,0.2) (0.3,0.6,0.1)	(0.2,0.6,0.2) (0.4,0.2,0.4)	(0.6,0.2,0.2) (0.1,0.9,0)	(0,1,0) (0.9,0.1,0)	(0.1,0.2,0.7) (0.8,0.1,0.1)	(0.6,0.2,0.2) (0.1,0.1,0.6)	(0.6,0.1,0.3) (0,0.4,0.6)	(0.2,0.2,0.7) (0.1,0.1,0.8)	(0.3,0.4,0.2) (1,0,0.8)	(0.5,0,0.5) (1,0,0)
A5	(0.3,0.3,0.4) (0.4,0.2,0.4)	(0.6,0.1,0.3) (0,0.2,0.8)	(0.7,0.2,0.1) (0.3,0.3,0.2)	(0.4,0.2,0.4) (0.7,0.1,0.2)	(0,0.2,0.9) (0,0.1,1)	(0.1,0.2,0.7) (0,0.1,0.9)	(0.2,0.1,0.7) (0.1,0.3,0.6)	(0.2,0.6,0.2) (0.1,0.7,0.2)	(0.3,0.4,0.3) (0.5,0.5,0)	(1,1,0) (0.7,0.9,0.2)

The Neutrosophic Normalized data is given by

$$NX_i^*(k) = 1 - \frac{(N_1 - N_2)x_i(k) - (N_1 - N_2)x_i min(k)}{(N_1 - N_2)x_i max(k) - (N_1 - N_2)x_i min(k)}$$

Here N_1 and N_2 are the Neutrosophic sets.
Take N_1 values from the tabular values and Assume that $N_2 = (1,1,1)$.

TABLE 11. Difference of Neutrosophic Sets

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0.6,0.7,0.1)	(0.4,0.2,0.6)	(0.1,0.3,0.2)	(0.2,0.3,0.1)	(0.4,0.1,0.6)	(0.7,0.3,0.4)	(0.5,0.1,0.6)	(0.1,0.5,0)	(0.3,0.2,0.1)	(0.3,0.1,0.2)
A2	(0.1,0.5,0.6)	(0.8,0.2,0.6)	(0.2,0.2,0)	(0.3,0,0.3)	(0.1,0.1,0)	(0.1,0.3,0.4)	(0.6,0,0.6)	(0.1,0.4,0.1)	(0.6,0.2,0.4)	(0.1,0.1,0.2)
A3	(0.2,0.5,0.1)	(0.5,0.4,0.4)	(0.1,0.2,0.1)	(0.1,0.6,0.1)	(0.6,0.1,0.2)	(0.5,0.2,0.3)	(0.5,0.4,0.6)	(0.6,0.6,0.1)	(0.1,0.3,0.4)	(0.2,0.2,0.4)
A4	(0.2,0.1,0.1)	(0.2,0.4,0.2)	(0.5,0.7,0.2)	(0.9,0.9,0)	(0.7,0.1,0.6)	(0.5,0.1,0.4)	(0.6,0.3,0.3)	(0.1,0.1,0.1)	(0.7,0.4,0.6)	(0.5,0,0.5)
A5	(0.1,0.1,0)	(0.6,0.1,0.5)	(0.4,0.1,0.1)	(0.3,0.1,0.2)	(0,0.1,0.1)	(0.1,0.1,0.2)	(0.1,0.2,0.1)	(0.1,0.1,0)	(0.2,0.1,0.3)	(0.3,0.1,0.2)

TABLE 12. Neutrosophic Normalized Data

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(0,0,0)	(0.7,0,0)	(0.7,0.8,0.5)	(1,1,1)	(0.4,1,0)	(0,0,0)	(0.2,0.5,0)	(1,0.2,0)	(0.8,0.7,0.3)	(0.5,1,1)
A2	(1,0.4,0.4)	(0,0, 0)	(1,1,1)	(0.9,0.5,1)	(0.9,1,0.8)	(1,0,0)	(0,0, 0)	(1,0.4,0)	(0.2,0.7,0.7)	(1,1,1)
A3	(0.8,0.4,0)	(0.5,1,0.5)	(0.7,1,0.5)	(0.9,0.5,1)	(0.1,1,0.8)	(0.3,0.3,0.5)	(0.2,0,0)	(0,0,0)	(0.8,0.3,0.7)	(0.7,0,0.3)
A4	(0.8,1,0)	(1,1,1)	(0,0,0)	(0,0,0)	(0,0, 0)	(0.3,1,0)	(0,0.5,0.6)	(1,1,0)	(0,0,0)	(0,0,0)
A5	(1,1,1)	(0.4,0,0.2)	(0.4,0.8,0.5)	(0.9,0.7,0)	(1,1, 1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(0.5,1,1)

TABLE 13. Neutrosophic Deviation Sequence

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	(1,1,1)	(0.3,1,1)	(0.3,0.2,0.5)	(0,0,0)	(0.6,0,1)	(1,1,1)	(0.8,0.5,1)	(0,0.8,1)	(0.2,0.3,0.7)	(0.5,0,0)
A2	(0.8,1,0.6)	(1,1,1)	(0,0,0)	(0.1,0.5,0)	0.1,0,0.2	(0,1,1)	(1,1, 1)	(0,0.6,1)	(0.8,0.3,0.3)	(0,0,0)
A3	(0.2,0.6,1)	(0.5,0,0.5)	(0.3,0,0.5)	(0.1,0.5,0)	(0.9,0,0.2)	(0.7,0.7,0.5)	(0.8,1,1)	(1,1,1)	(0.2,0.7,0.3)	(0.3,1,0.7)
A4	(0.2,0.9, 1)	(0,0,0)	(1,1,1)	(1,1,1)	(1,1, 1)	(0.7,0,0)	(1,0.5,0.4)	(0,0,1)	(1,1,1)	(1,1,1)
A5	(0,0,0)	(0.6,1,0.8)	(0.6,0.2,0.5)	(0.1,0.3,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(0.5,0,0)

TABLE 14. Neutrosophic Grey Relational Coefficient Between Two Sets

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	0.2240	0.4066	0.6489	1.0000	0.7197	0.2242	0.3756	0.5036	0.5980	0.7739
A2	0.3491	0.2242	1.0000	0.7518	0.8700	0.4826	0.2242	0.5331	0.5525	1.0000
A3	0.4950	0.6467	0.7000	0.7518	0.6255	0.4314	0.2756	0.2242	0.5980	0.4419
A4	0.4416	1.0000	0.2242	0.2242	0.2242	0.5173	0.4541	0.6472	0.2242	0.2242
A5	1.0000	0.3499	0.5727	0.5664	1.0000	1.0000	1.0000	1.0000	1.0000	0.7739

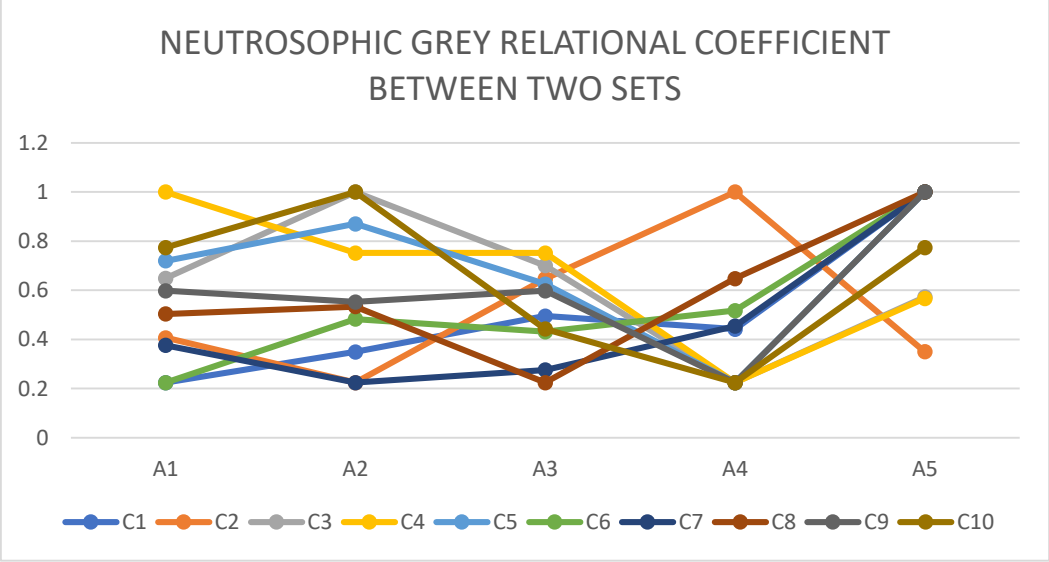

FIGURE 7.

TABLE 15. Neutrosophic Grey Relational Analysis Between Two Sets

$A1$	0.54745
$A2$	0.59875
$A3$	0.51901
$A4$	0.41812
$A5$	0.82629

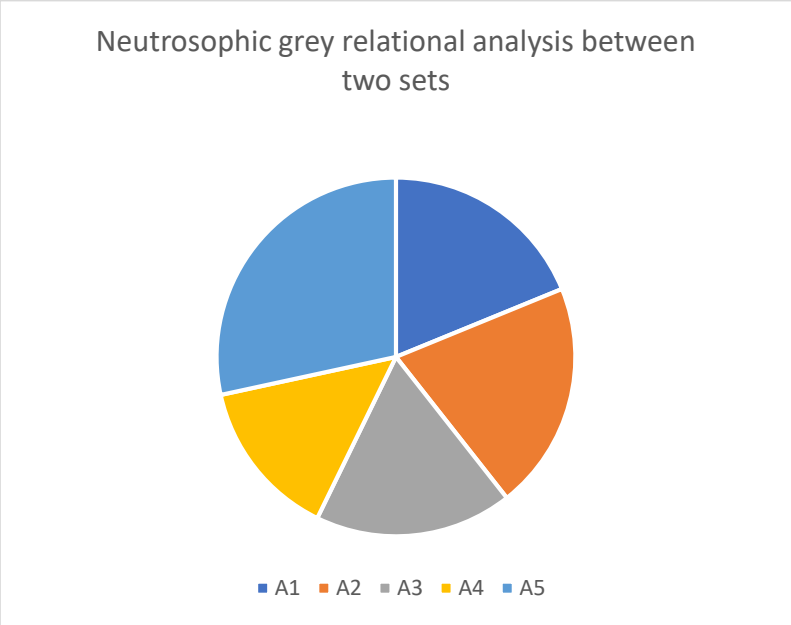

FIGURE 8. Neutrosophic Grey Relational Analysis Between Two Sets

TABLE 16. Ranking

$A1$	Ependymoma (EPN)	3
$A2$	Pineal Tumour(PT)	2
$A3$	Medulloblastoma(MDB)	4
$A4$	Glioblastoma(GBM)	5
$A5$	Meningioma(MNG)	1

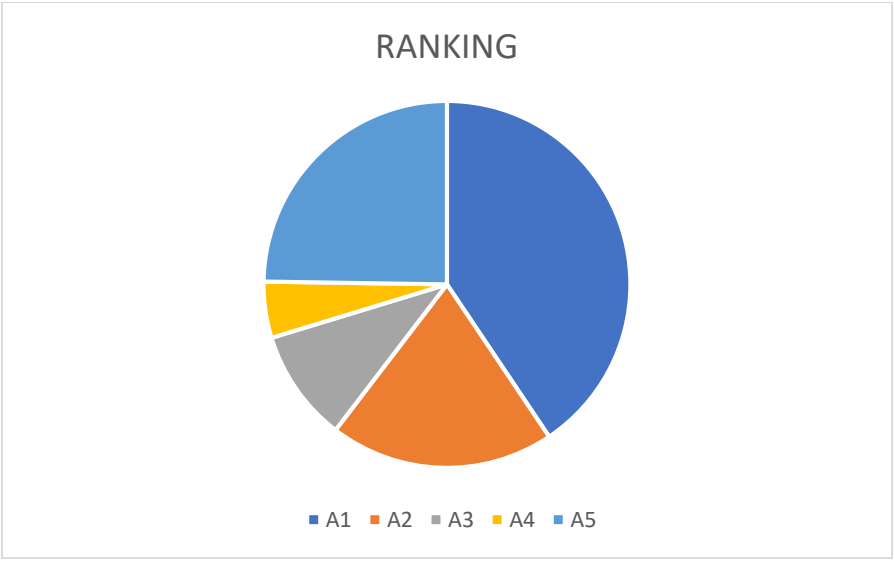

FIGURE 9. Ranking

The above table shows the rank. Here Meningioma (MNG) is first ranking and also a low affect disease. Glioblastoma (GBM) is a last ranking disease and it is high affect disease.

Comparisons Analysis:

Brain cancer metastasis is a complex and multifaceted problem that requires careful analysis and decision making. Both MCDM method and Neutrosophic set can be used to analyze and evaluate the metastasis of brain cancer. Here's a comparision analysis between two approaches are MCDM method and Neutrosophic set.

MCDM methods are a class of decision-making techniques that evaluate multiple criteria to make a decision. In the context of brain cancer metastasis, MCDM methods can be used to evaluate the likelihood of metastasis based on multiple criteria.

Neutrosophic sets are a mathematical framework for representing and analyzing uncertain, imprecise, and incomplete information. In the context of brain cancer metastasis, Neutrosophic sets can be used to represent the uncertainty and ambiguity associated with the metastasis process using three components are Truthiness(T), Falsity(F), Indeterminacy(I).

Here's a comparison analysis between MCDM methods and Neutrosophic sets in brain cancer metastasis:

- Handling uncertainty: Neutrosophic sets are better equipped to handle uncertainty, ambiguity, and imprecision in the data, whereas MCDM methods rely on crisp and precise data.
- Flexibility: Neutrosophic sets offer more flexibility in representing and analyzing uncertain and imprecise information, whereas MCDM methods are more structured and rigid.
- Interpretability: MCDM methods provide more interpretable results, whereas Neutrosophic sets require more expertise and knowledge to interpret the results.
- Computational complexity: MCDM methods are generally more computationally efficient than Neutrosophic sets, especially for large datasets.
- Applicability: Both MCDM methods and Neutrosophic sets can be applied to brain cancer metastasis, but Neutrosophic sets may be more suitable for representing and analyzing uncertain and imprecise information.

8. CONCLUSION

In MCDM method ranked the disease using GREY RELATION ANALYSIS and it says that Meningioma(MNG) is low affecting brain cancer and Glioblastoma (GBM) is most aggressive brain cancer. Neutrosophic set ranked the disease using NEUTROSOPHIC GREY RELATION ANALYSIS and this method also says that most affecting brain cancer is Glioblastoma and least affecting is Meningioma .

Both MCDM methods and Neutrosophic sets can be effectively used to analyze brain cancer metastasis. However, Neutrosophic sets are better suited for handling uncertainty, ambiguity, and imprecision in medical data. MCDM methods, on the other hand, provide more interpretable results and are computationally efficient. A hybrid approach combining the strengths of both methods could provide a more comprehensive and accurate analysis of brain cancer metastasis. Further research is needed to explore the potential of Neutrosophic sets and MCDM methods in medical decision-making and to develop more effective hybrid approaches.

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