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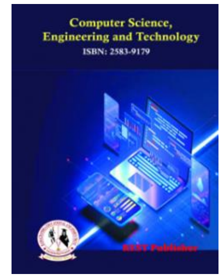

Soft Computing Paradigms for Medical Decision Support: A Multi-Criteria WSM Analysis

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Abstract: Accurate and rapid diagnosis of brain tumors remains a significant challenge in modern clinical settings. While histological analysis remains the gold standard for diagnosis, issues such as limited access to anatomical data or the need for additional validation highlight the need for alternative computational approaches. This research explores the combined use of in vitro ^{1}H magnetic resonance spectroscopy (MRS) and soft computing (SC) methods to facilitate non-invasive tumor detection and classification. Soft computing methods such as fuzzy logic, neural networks, and evolutionary algorithms and probabilistic models – provide adaptive, cost-effective, and resilient solutions by managing imprecision and uncertainty in a way that mimics human reasoning. The focus of this study is the Adaptive Neuron-Adaptive Neuron- Fuzzy Inference System (ANFIS) is used to model complex nonlinear diagnostic relationships and aid decision making under uncertainty. Furthermore, multiple criteria decision making (MCDM) approaches - in particular weighted sum model (WSM) - are used. fine-tune diagnostic decisions based on various clinical and computational parameters. The integration of SC and MCDM provides a robust decision-support framework capable of managing complex and ambiguous clinical data. This method not only complements histological assessments, but also improves diagnostic reliability in situations where conventional histopathology is limited or unavailable.

Keywords: *Soft Computing Techniques, Magnetic Resonance Spectroscopy (MRS), Weighted Sum Model (WSM), Brain Tumor Classification, Uncertainty Handling in AI.*

1. INTRODUCTION

The development of non-histological diagnostic techniques Paraphrasing using in vitro ^{1}H magnetic resonance spectroscopy (MRS) of the human brain. tumor specimens are a major focus in clinical practice. Although histological analysis is essential for definitive tumor diagnosis, computational methods can serve as valuable adjunct tools - especially when independent confirmation is required or when accurate anatomical assessment is challenging. [1]Tumor classification involves a complex combination of histopathological features, clinical assessments, and tissue morphological analysis. Because the grading process involves diverse and complementary diagnostic criteria, the accuracy of histological assessment relies heavily on the expertise and judgment of pathologists. [2] An indirect measurement method determines individual stages by analyzing time-varying signals received from a set of sensors. [3]Soft computing research focuses on combining artificial Paraphrasing intelligence techniques such as neural networks, fuzzy logic, and evolutionary algorithms. - into complementary hybrid systems that address real-world challenges. There are various methods for building neuron-fuzzy systems by integrating neural networks with fuzzy logic. This study focuses on a basic neuron-fuzzy model called the Adaptive A brief description of the Neuron-Fuzzy Inference System (ANFIS) is provided. ANFIS was initially used to model the nonlinear dynamics of the knee joint using recorded clinical data the acronym Soft Computing (SC) refers to a growing set of algorithms designed to handle imprecision and uncertainty, aiming for robust, efficient, and cost-effective solutions. And tolerance for partiality h. SC offers an attractive opportunity to represent the ambiguity inherent in human thinking with real-life uncertainty. [5] Infrastructure management tasks Processes such as condition assessment, performance forecasting, requirement assessment, prioritization, and optimization often rely on uncertain, ambiguous, or incomplete data. As a result, these processes require engineering judgment and expert insight to navigate the inherent uncertainties and make informed decisions. Soft computing methods are particularly well suited to dealing with imprecise, uncertain, ambiguous, incomplete, or subjective data. [6] Soft computing is an emerging field that integrates various complementary techniques, including fuzzy logic, neural networks, and evolutionary algorithms. These techniques have been applied in many domains, with edge detection for image segmentation standing out as one of the most notable applications. [7]A comprehensive evaluation of existing software techniques and their application in infrastructure management has shown that they effectively support various management functions. In particular, life cycle cost analysis (LCCA) relies on information derived from existing datasets and expert judgments, which are often uncertain, ambiguous, or incomplete. [8]. Soft Computing (SC) is a growing set of algorithms designed to provide robust, adaptive, and cost-effective solutions by accepting imprecision, uncertainty, and partial truths. It offers a promising approach to modeling the ambiguity found in human reasoning and the uncertainty present in real-world situations. [9] This paper presents a review of the current literature on data mining techniques using soft computing. It categorizes the approaches based on specific soft computing methods and their hybrids, the data mining tasks performed, and the chosen evaluation criteria of the model. [10] A soft computer consists of a group of algorithms designed to ensure practicality, robustness, and cost-effectiveness while considering imprecision and uncertainty Its main components include fuzzy logic, neural networks, and probabilistic reasoning. [11]Soft computing is the science of reasoning, inference, and decision-making that acknowledges and applies real-world concepts such as grouping, membership, and classification at various levels of analysis. It extends natural heuristic approaches and is well suited to managing complex systems because it operates without the need for strict mathematical definitions or precise distinctions between system components.[12] Soft computing is gradually revealing new avenues in bioinformatics by providing cost-effective, approximate solutions that are useful in practice. This approach encompasses a variety of paradigms, including fuzzy sets (FSs), artificial neural networks (ANNs), evolutionary algorithms, approximate sets (RSs), and support vector machines (SVMs).

2. MATERIEAL METHODS

Deep Learning: Deep learning is an artificial intelligence (AI) approach that helps computers interpret data by imitating the way the human brain works. These models are capable of recognizing complex patterns in images, text, audio, and other data types and generating reliable insights and predictions. Swarm Intelligence: Swarm intelligence refers to a decentralized, self-organizing approach to collective learning and decision-making. It is commonly seen in nature - for example, in flocks of birds or schools of fish - where they move and respond as integrated units without centralized control or leadership.

Evolutionary Computation: Evolutionary computation, a branch of artificial intelligence (AI), is commonly used to tackle complex and persistent optimization challenges. It is particularly useful for solving problems involving a large number of variables, where conventional methods are inadequate

Probabilistic Reasoning: Probability theory serves as the foundation upon which AI and machine learning models are built, providing a language for quantifying uncertainty, expressing randomness, and explaining causality about the probabilities of events.

Reinforcement Learning: Reinforcement learning is a subset of machine learning in which an agent learns to make decisions by interacting with its environment through trial and error, aiming to maximize overall rewards. This approach mirrors the way humans and animals learn from the consequences of their actions and adjust behavior based on the rewards or punishments received. For instance, a robot might figure out how to move through a maze by earning rewards for reaching the end and facing penalties when it bumps into walls.

Flexibility: System flexibility refers to the ability of any primary component in a digital system to manage uncertainty when interacting with other key components via the data path.

Tolerance for Approximation: A soft computer differs from a conventional (hard) computer in that, unlike a hard computer, it tolerates imprecision, uncertainty, partial truth, and approximation. In fact, the prototype for a soft computer is the human mind.

Handling uncertainly: Information intended to reduce uncertainty is called uncertainty-oriented information. Its properties are determined by a mathematical theory that defines the uncertainty in various problem-solving situations.

Computational Efficiency: Maximizing the effective use of computational resources improves performance and reduces waste. In computing and artificial intelligence, computer performance is a key indicator of how efficiently hardware and software are used to complete tasks.

WSM Method: In recent years, multi-criteria decision-making (MCDM) methods have gained prominence as useful tools for addressing complex real-world challenges. Their effectiveness stems from their ability to evaluate multiple alternatives against a variety of criteria to determine the most appropriate choice. In this study, several MCDM techniques were used to optimize multiple response variables. Among the various multi-criteria decision-making (MCDM) techniques, the weighted sum method (WSM) is recognized as one of the earliest and most widely used approaches. This paper examines the application of MCDM methods, particularly WSM, to assess employee competency in the apparel industry. By assessing multiple criteria, these methods aim to facilitate the selection of the most suitable operators from a set of candidates.To address the challenge of employee selection, both the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) were used. These methods aim to help identify the most competent operator among multiple candidates' is a machine-level, procedural programming language commonly used to develop a wide range of applications and operating systems, such as Windows. It is the foundation for more complex software, including the Oracle Database, Get, the Python interpreter, and various computer games. C is a popular choice among programmers, especially for low-level and system programming tasks, due to its structured programming approach. Breast cancer usually develops in a localized area, but can metastasize to lymph nodes and distant organs. At the time of initial diagnosis, prognostic markers play an important role in assessing the extent of systemic disease. The prevailing model of metastasis adopts a phenotypic perspective rooted in the genetic makeup of breast tissue, which supports the idea that some cancer cells may have the ability to spread. [21]In supply chain management, selecting alternative suppliers to meet customer demand is a critical consideration for any organization. While there are several methods for identifying the most suitable suppliers—ultimately aiming to improve customer satisfaction and increase organizational productivity—this research focuses on the application of MOORA and the Weighted Sum Method (WSM) for supplier evaluation. An integrated approach was implemented using both methods, and the results are presented and analyzed in the Results and Discussion sectionThis paper assesses the conservatism in the design of geosynthetic reinforced soil walls within North American engineering practices, focusing on internal stability. The assessment uses data from closely monitored geosynthetic structures across North America, Europe, and Scandinavia, as well as full-scale laboratory wall tests conducted at the Royal Military College (RMC) of Canada.). [23] Lasers are essential medical tools commonly used in surgical procedures for a variety of purposes, including treating damaged blood vessels, reducing blood loss, and reducing the risk of infection. There are different types of lasers, classified according to the materials used in their construction. As a result, choosing the appropriate type of laser is of paramount importance when performing complex surgical tasks. The system discussed here is designed to provide multi-partner recommendations this study uses a systematic approach by integrating the fuzzy analytic hierarchy process (F-AHP) and the weighted sum model (WSM) to improve decision-making processes. Within this framework, the F-AHP is used to assign weights to primary criteria, while the WSM evaluates the sub-criteria, which facilitates a more accurate matching process. Furthermore, a comparative analysis was conducted to evaluate the performance of various multi-criteria decision-making (MCDM) methods, including the weighted product model (WPM), the weighted sum model (WSM), the modified analytic hierarchy process (AHP), the technique for ordering prioritization by similarity to the ideal solution (TOPSIS), and the complex proportionality estimation (COPRAS). The aim is to evaluate the performance of these techniques in a standard housing affordability assessment model. The findings suggest that COPRAS may be more suitable for such assessments due to its ability to handle both benefit and cost criteria and its straightforward application. The evaluation involved analyzing ten different areas in Liverpool, England, using defined criteria to examine the applicability of each MCDM method to a specific decision-making problem. The latest edition of the Code of Practice for General Steel Construction, IS 800:2007, introduces a limit state design method, which represents a significant change from the older IS 800:1984 standard, which was based on the elastic design method. The study provides a comprehensive analysis of structural elements designed as tension members using both the limit state and working stress methods. The comparative results are illustrated with graphs and charts, highlighting the cost-effectiveness and benefits of the limit state design approach in various structural segmentsMulti-criteria decision analysis (MCDA), also known as multi-criteria decision making (MCDM), is a subfield of operations research that explicitly evaluates multiple conflicting criteria in decision making. This approach is particularly useful when criteria such as cost and quality are in conflict, necessitating a balanced assessment to achieve the optimal decision. This paper presents a case study that evaluates a systematic method for selecting reusable off-the-shelf (COTS) software. It discusses common challenges encountered during software selection, outlines the adopted method, and analyzes the case study results. To improve the traditional probabilistic life cycle cost analysis (LCCA) model, a fuzzy logic-based approach was integrated into the risk assessment process. This improved model helps determine the optimal timing for pavement maintenance, rehabilitation, and reconstruction (MR&R) treatments. By using performance curves and fuzzy logic-based stimulus models, the new method supports more effective planning of pavement interventions. Fuzzy Logic introduces essential concepts such as fuzzy set theory, fuzzy if-then rules, and approximate reasoning, which help better handle uncertainty and data granularity. Neural networks provide adaptive learning by adjusting internal connections, while genetic algorithms use a structured random search process, making them valuable tools for optimization tasks.

3. RESULT AND DISCUSSION

TABLE 1. soft computing

	Flexibility	Tolerance for Approximation	Handling uncertainly	Computational Efficiency
Deep Learning	25.000	56.000	30.000	65.000
Swarm Intelligence	28.000	86.000	63.000	99.000
Evolutionary Computation	30.000	82.000	75.000	85.000
Probabilistic Reasoning	41.000	65.000	91.000	80.000
Reinforcement Learning	42.000	11.000	55.000	84.000

Table 1 provides a comparative overview of various soft computing techniques on four key criteria: flexibility, approximation tolerance, uncertainty management, and computational efficiency. Swarm intelligence performs particularly well in managing uncertainty and tolerating approximation, while deep learning stands out for its high computational efficiency.

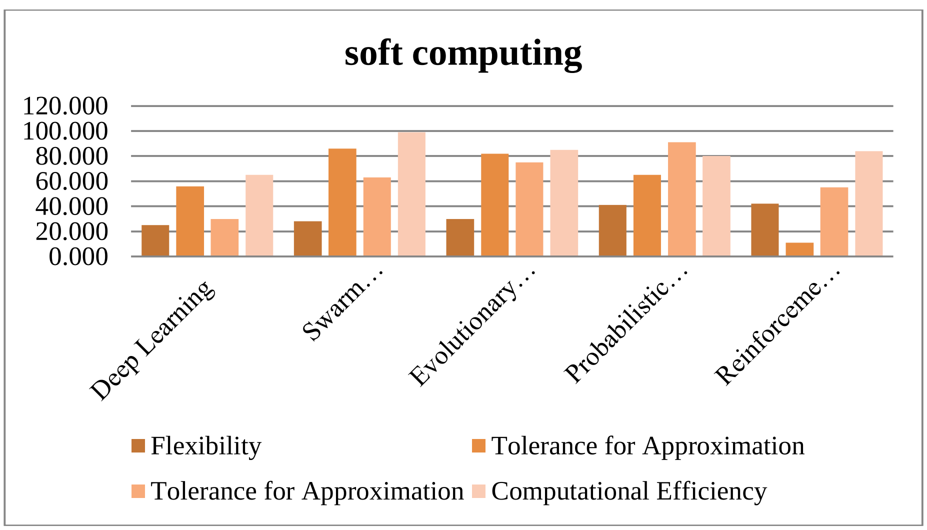

FIGURE 1. soft computing

Figure 1 illustrates how different soft computing methods interact with each other using the Weighted Sum Model

(WSM). Swarm intelligence achieves the highest overall performance, offering a strong balance of flexibility, tolerance for approximation, and efficiency. Evolutionary computation and probabilistic reasoning perform well on many scales. In contrast, reinforcement learning, while efficient, demonstrates limited tolerance for approximation.

TABLE 2. Normalized

	Normalized			
Deep Learning	0.59524	0.65116	1.00000	1.00000
Swarm Intelligence	0.66667	1.00000	0.47619	0.65657
Evolutionary Computation	0.71429	0.95349	0.40000	0.76471
Probabilistic Reasoning	0.97619	0.75581	0.32967	0.81250
Reinforcement Learning	1.00000	0.12791	0.54545	0.77381

Table 2 shows the performance of soft computing techniques based on normalized weighted ensemble model (WSM) values. Deep learning and reinforcement learning scored the highest in normalized performance. Swarm intelligence stands out in terms of approximation tolerance, while evolutionary computation consistently provides balanced performance. Probabilistic reasoning shows strong flexibility but falls short in managing uncertainty, highlighting the varying strengths of each computational approach.

TABLE 3. weight

	Weight			
Deep Learning	0.25	0.25	0.25	0.25
Swarm Intelligence	0.25	0.25	0.25	0.25
Evolutionary Computation	0.25	0.25	0.25	0.25
Probabilistic Reasoning	0.25	0.25	0.25	0.25
Reinforcement Learning	0.25	0.25	0.25	0.25

Table 3 uses equal weighting for all criteria within the WSM framework, considering flexibility, approximation tolerance, uncertainty handling, and computational efficiency as equally important. This balanced approach enables an unbiased comparison of soft computing methods, allowing for an overall performance determination based on their inherent strengths without favoring any particular evaluation factor.

TABLE 4. weighted normalized decision matrix

	Weighted normalized decision matrix			
Deep Learning	0.14881	0.16279	0.25000	0.25000
Swarm Intelligence	0.16667	0.25000	0.11905	0.16414
Evolutionary Computation	0.17857	0.23837	0.10000	0.19118
Probabilistic Reasoning	0.24405	0.18895	0.08242	0.20313
Reinforcement Learning	0.25000	0.03198	0.13636	0.19345

Table 4 to assess the interaction, the weighted normalized result matrix obtained using the weighted sum method (WSM) is shown. Deep learning performs strongly on two criteria (0.25 each), whereas probabilistic reasoning and reinforcement learning demonstrate significant strengths in specific areas. Swarm intelligence and evolutionary computation show more evenly distributed, moderate scores, indicating well-rounded contributions across different interoperability dimensions.

TABLE 5. preference score

	Preference Score
Deep Learning	0.81160
Swarm Intelligence	0.69986
Evolutionary Computation	0.70812
Probabilistic Reasoning	0.71854
Reinforcement Learning	0.61179

Table 5presents the preference scores of various AI paradigms evaluated using the Weighted Sum Model (WSM) method. Deep Learning achieves the highest score at 0.81160, indicating its superior performance across the assessed criteria. Probabilistic Reasoning (0.71854), Evolutionary Computation (0.70812), and Swarm Intelligence (0.69986) follow, reflecting moderate effectiveness. Reinforcement Learning scores lowest at 0.61179, suggesting relatively lesser suitability in this context.

TABLE 6. rank

	Rank
Deep Learning	**1**
Swarm Intelligence	**4**
Evolutionary Computation	**3**
Probabilistic Reasoning	**2**
Reinforcement Learning	**5**

Table 6 outlines the rankings obtained from the WSM method. Deep learning takes the top spot according to its highest preference score. Probabilistic reasoning takes second place, followed by evolutionary computation in third place. Swarm intelligence takes fourth place, and reinforcement learning takes last place, indicating the lowest preference among the methods evaluated.

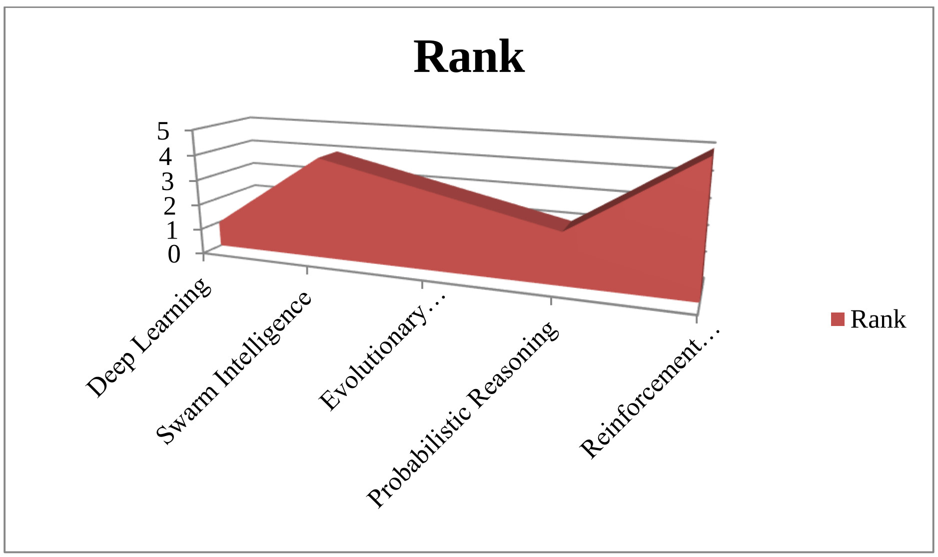

FIGURE 2. rank

Figure 3 shows the rankings of various AI paradigms determined by the Weighted Sum Model (WSM) method. Deep learning claims the highest rank (rank 1), highlighting its excellent performance on the assessed criteria. Probabilistic reasoning is in second place, with evolutionary computation and swarm intelligence taking third and fourth places, respectively. Reinforcement learning is in fifth place, indicating relatively low performance in this assessment.

4. CONCLUSION

The application of soft computing techniques to non-histological diagnostic approaches – particularly in the use of in vitro ¹H MRS biopsies for the diagnosis of human brain tumors – offers a compelling alternative to conventional histological methods. Although histopathological evaluation is the clinical standard, the reliance on expert interpretation and the need for adequate tissue samples highlight the potential value of computational diagnostic aids. Soft computing, with its inherent ability to manage uncertainty, imprecision, and approximation, provides powerful support for improving diagnostic accuracy and facilitating informed decision-making in data-intensive and complex clinical settings. Each of the soft computing paradigms examined – deep learning, swarm intelligence, evolutionary computation, probabilistic reasoning, and reinforcement learning – offers unique advantages. Deep learning stands out for its superior computational power and overall performance, as reflected in its leading scorer in Weighted Sum Model (WSM) analysis. Probabilistic reasoning stands out for its adaptability and interpretability, making it a valuable tool in uncertain environments. On the other hand, evolutionary computation provides consistently balanced results across a variety of evaluation scales. Swarm intelligence shows strong tolerance for approximation, while reinforcement learning, despite its low performance in approximation, excels in computational performance and decision-making tasks. The weighted sum model (WSM) provides a clear and structured approach to evaluating these soft computing paradigms, enabling comparisons across important factors such as flexibility, approximation tolerance, uncertainty handling, and performance. By weighting these criteria equally, the evaluation maintains objectivity and avoids favoring any one performance dimension. In summary, this multi-criteria analysis emphasizes the promising role of soft computing in complementing conventional diagnostic methods, especially in situations characterized by ambiguous, incomplete, or complex data. As the field progresses, the development of hybrid systems and the integration of soft computing with domain-specific expertise is expected to further enhance its relevance and effectiveness in areas such as biomedical diagnostics and infrastructure management.

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