

RESEARCH ARTICLE

Enhancing Decision Support Systems Through Deep Learning and the EDAS Multi Criteria Decision Making Method

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ABSTRACT: This paper presents a comprehensive exploration of the integration between deep learning methodologies and Various multi-criteria decision making (MCDM) techniques, with a particular focus on the EDAS (Estimation Based on Distance from Average Solution) method recent years, deep learning has made significant progress, driven by increased computational power and the availability of large-scale datasets. This technological evolution has transformed how machines process and interpret various data types, including images, text, and speech, with applications spanning healthcare, ophthalmology, remote sensing, and drug discovery. The research examines Various deep learning frameworks, including deep feed-forward networks, Boltzmann machines, auto encoders, and recurrent neural networks, and their operational mechanisms. Simultaneously, we investigate the EDAS method's versatility in addressing complex decision-making scenarios across multiple domains. Originally developed for inventory classification, EDAS evaluates alternatives Evaluating alternatives by measuring Their deviations from the average solution are both positive and negative, making it particularly valuable in uncertain environments where precise evaluations are challenging. Our analysis identifies significant challenges in both fields: deep learning confronts issues related to data management, privacy concerns, and preprocessing requirements, while MCDM methods struggle with adaptability when alternatives are modified and expression constraints in fuzzy extensions. We discuss emerging solutions, including transfer learning approaches, Bayesian optimization techniques, and EDAS modifications incorporating various distance metrics to enhance robustness in decision-making processes. The paper highlights practical applications across diverse sectors, from battery technology selection and agricultural planning to e-learning evaluation and human resource management, demonstrating the broad applicability of these integrated approaches. We conclude that the combination of deep learning's pattern recognition capabilities with MCDM's structured evaluation frameworks offers promising pathways for addressing increasingly complex decision-making challenges in data-rich environments. This integration presents significant opportunities for advancement in multiple fields, potentially revolutionizing how complex problems are approached and solved in both research and practical applications.

Keywords: Deep Learning, MCDM (Multi-Criteria Decision Making), Multimodal Learning, Healthcare Applications, Transfer Learning.

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1. INTRODUCTION

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Multimodal learning combines information from multiple sources. For example, images and 3D depth scans exhibit first-order correlations, as depth discontinuities often appear as strong edges in images. In contrast, audio and visual data for speech recognition share “middle-order” correlations, as phonemes correspond to lip movements and poses, making it challenging to directly associate source pixels with audio waveforms or spectrograms. This study focuses on modeling

these “middle-order” relationships using audio-visual speech recognition to validate the proposed methods. [1] It is true that Practitioners can gain general knowledge in these subjects through a variety of resources, including training programs, books, and other materials and other materials. However, the vast array of available algorithms and health monitoring solutions complicates the effective processing and use of this information. This creates a gap because a wide range of solutions require decision-making, for which engineers may not be fully prepared. This article seeks to bridge that gap. Advances in health monitoring methods and diagnostic technologies for space applications represent a significant advance, challenges and demands of such environment harsh environments in which these assets operate. [2] Survey workflows are facing significant.

The increasing demand for improved performance at low cost, combined with the vast amounts of data generated by advanced sensors and modern acquisition systems, is creating significant pressure. One of the primary challenges is that experts have limited time, while the amount of data requiring in-depth analysis continues to expand. Furthermore, the complexity of some research fields requires greater attention and meticulous examination. Ultimately, this problem can be characterized as the increasing complexity of data, which poses challenges to efficient processing, interpretation, and decision-making in various fields. [3] This paper presents a comprehensive review of current research on Deep learning models and their applications in medical and health monitoring systems are explored, along with recent challenges related to these models. Insights are provided to help the research community address these issues.

The rest of this research paper is organized as follows: Section X presents an overview of deep learning research models, describing their network architectures and essential properties. In addition, this section explores the various available deep learning architectures and the platforms they support, providing a broad overview of their implementation and accessibility. [4] Deep learning, a specialized branch of machine learning (ML), experienced a significant renaissance in recent years, primarily driven by improved computational power and the abundance of large-scale datasets. The field has made significant progress in helping machines interpret and process various types of data, including images, text, and speech. With the vast amount of data being produced in the US alone, measured in Exabyte's and expanding annually, along with the growing adoption of medical devices and digital systems of record, the healthcare and medical sectors are poised to reap significant benefits from deep learning. [5] Ophthalmologists diagnose diseases by recognizing patterns through direct or indirect visualization of the eye and its surrounding structures.

Diagnostic technologies in ophthalmology enhance this process by digitally representing these structures, providing additional insights to physicians. Ophthalmology is particularly well-positioned to benefit from deep learning (DL) algorithms, given its reliance on imaging. The integration of DL into ophthalmology practice has already begun and has the potential to fundamentally change the

nature of ophthalmologists' work. [6] In practice, remote sensing (RS) images often fail to meet the desired quality due to various factors such as sensor limitations and atmospheric interference. As a result, RS Image preprocessing is a necessary step to improve image quality before performing classification and recognition tasks. As pointed out in the relevant remote sensing (RS) literature, most studies emphasize the importance of preprocessing techniques to improve image clarity, reduce noise, and improve the overall accuracy in subsequent analysis current techniques for noise removal, de-blurring, super-resolution, and pan-sharpening rely on conventional image processing methods from the field of signal processing, while machine learning-based approaches are relatively rare. [7] In deep learning, the term "deep" refers to the increasing number of layers of a neural network that are added over time. The process involves two main stages: the training phase and the inference phase.

During training, the model processes a large amount of data to improve its learning and accuracy learn complex patterns and features datasets are labeled and their relevant features are identified. The inference phase involves making decisions based on prior knowledge and labeling new, unseen data. Deep learning systems enable complex cognitive tasks to be handled with a high degree of accuracy. [8] With the advent of advanced Numerous researchers have approached The SAR-ATR problem has been solved using machine learning techniques, including robust classifiers such as support vector machines (SVM) and boosting matching features extracted from a test target with a template database or CAD model predictions, the recognition task is redefined. It focuses on designing various feature extractors to represent the targets, followed by training a classifier using these feature vectors for accurate identification. [9] The public's the Talisman-Problem QAR Merck's machine learning challenge in drug discovery has received significant attention. The competition aimed to predict drug properties and activity, and a deep learning network emerged as the winner. It showed a significant improvement in accuracy compared to Merck's in-house systems, highlighting Deep learning capabilities in drug discovery. Achievement this approach was even featured in The New York Times. In this work, we present Recent advances in chemistry-based research highlight significant progress in machine learning techniques, especially deep learning.

This paper highlights recent progress in this field, explores its potential applications, and discusses future developments of this revolutionary technology in drug discovery. [10] Transfer learning (TL) is a widely used and effective approach to extract common features from a large dataset, which can then be used for secondary tasks on a smaller data set. First, a model is trained on a large dataset, followed by fine-tuning on a smaller, more specific dataset desirable properties, which improves the generation of more reliable molecules. In contrast, Bayesian optimization (BO) is a structured hierarchical method aimed at globally optimizing black-box functions, often using the Gaussian process (GP) serves as a flexible model to represent any smooth, continuous function with a minimum number of

parameters. [11] Instead, we emphasize the various data management challenges that deep learning (DL) experts face when Building Deep Learning Application Models. This paper explores various Examples of applications of deep learning frameworks, identification of key challenges, and classification based on the developmental stage at which they occur. This paper makes two primary contributions. First, it emphasizes the importance of data Challenges to be addressed in data management overcome to build efficient and effective deep learning models. [12] A machine is trained using a dataset helps the model to improve its performance gradually. When an input is given, a function processes it, passes the data through several layers, and converts it into an output.

The model then evaluates the predicted output against the actual result, determining the discrepancy. To reduce this difference, the output is propagated back through the model, which allows it to adjust and improve its accuracy. [13] Traditional machine learning techniques have had limited ability to process real-world data in its raw form. As a result, designing a feature extractor required years of expertise and effort to transform the raw data into an appropriate representation, or feature vector, so that the machine could classify patterns in the input. In deep learning, Multiple layers between input and output are used for feature extraction and processing, which work in a similar way to the human brain.

Deep learning techniques belong to the field of representation learning, where nonlinear blocks structured into multiple layers, gradually transforming lower-level representations into higher-level abstractions. [14] The success of deep learning has led to a large number of Deep learning algorithms are used extensively in many fields and industries services that process high-dimensional and often sensitive user data, including speech, images, medical records, financial details, social interactions, and location data. This paper explores an important question: What privacy risks do deep learning algorithms pose to individuals whose data is used to train neural networks? More specifically, it aims to assess the extent of information leakage from these algorithms in relation to the individual training data models they use. [15]

2. MATERIALS AND METHOD

2.1. Deep feed-forward network

A deep feed-forward network (DFN) is a neural network model in which information flows in one direction, passing through an input layer, several hidden layers, and finally reaching the output layer without any loops or cycles, which input data moves through multiple layers in a single direction, passing through a function f^* . Unlike continuous networks, DFNs do not have a feedback mechanism, meaning there are no connections back to previous layers.

2.2. Deeply controlled Boltzmann machine

A Deep Boltzmann Machine (DBM) is a multi-layer neural network in which nodes are interconnected in different layers, which helps in hierarchical feature extraction from input data. The output of each layer serves as input for the next layer, allowing the model to capture complex patterns in which nodes are interconnected in various configurations. It extracts hierarchical features from input data, with the output of each layer serving as input to the next layer.

2.3. Deep automatic encoder network:

An autoencoder is a deep learning model that examines input data from various angles and contexts, enabling an accurate reconstruction of the original content. To create a deep fake using an autoencoder, two pairs of encoders and decoders are necessary.

2.4. Recurrent neural network

A recurrent neural network (RNN) is a type of deep learning model designed to process continuous data by maintaining connections between previous and current inputs. It is particularly useful for tasks involving temporal dependencies, such as natural language processing and time series analysis designed to handle continuous data and produce related continuous outputs. This data type, including words, sentences, or time series, exhibits complex semantic and syntactic relationships, making RNNs well suited to processing such dependencies particularly useful for capturing these dependencies.

2.5. Layered neural network

The layered approach integrates multiple devices or modules into a structured, hierarchical system. This method improves scalability and system expansion while minimizing the need for significant changes to existing infrastructure.

2.6. Virtual Screening AR Podium Mine

Virtual screening (VS), or computational screening, is a technique that analyses compound molecules using computational methods before conducting biological activity tests. This initial screening reduces the number of compounds tested and improves the efficiency of lead compound identification.

2.7. ADMT properties

Chemical absorption, distribution, metabolism, excretion, and toxicity (ADMET) are important considerations in drug

discovery and development. An ideal drug candidate should not only effectively target the intended therapeutic site, but also exhibit favorable ADMET properties at a therapeutic level development. An ideal drug candidate should not only effectively target the intended therapeutic, but also exhibit desirable ADMET properties at a therapeutic level.

2.8. Protein structure and function

Proteins are polypeptides composed of long chains of one or more amino acid residues. They play an important role in various biological functions, including: DNA replication, molecular transport, catalysis of metabolic reactions, and maintenance of cell structure.

2.9. Other applications

They are used in various fields Applications include Scientific research, business applications, office automation, digital work environments, inventory control, sales, finance, insurance, stock market trading, industrial processes, aerospace developments, and telecommunications.

2.10. EDAS method

Although various approaches have been developed to address stochastic MCDM problems, most approaches do not effectively integrate the key properties of statistical distributions with MCDM methods. As a result, existing techniques often involve complex calculations to provide robust They are used in various fields These include fields Including scientific research, business applications, office automation, and many other fields, digital workplaces, inventory management, sales, banking, insurance, stock trading, industrial operations, aerospace engineering, and communications. [16] As a result, it is expected that the EDAS method will be applied to various MCDM problems in the future. However, many real-world decision-making situations take place in uncertain environments, where it is challenging to define precise alternative evaluations and criterion weights. In such situations, conventional MCDM methods, which rely on unambiguous evaluation values, often struggle to provide adequate and useful decision-making results. [17] With the large number of vendors in the power industry, selecting the right battery energy storage system (BESS) from the available options is complex.

To address this challenge, this research aims to help readers by introducing a decision support system (DSS) that combines MCDM techniques - specifically CRITIC and EDAS - and uses a hybrid computational approach to determine the most appropriate BESS technology easily and directly select the optimal battery technology from a battery stack and performance-based manner. [18] This paper introduces a decision-making approach based on an example from agricultural practices. It examines different crops with

different growth periods and water requirements in a specific agricultural area, while assessing their economic feasibility. By following a predetermined cropping pattern and using drip and flood irrigation methods, data on nine distinct crop types are analyzed for their growth period, yield, water costs, and overall water consumption. [19] Apart from the main Considerations.

The remainder of this paper is structured into four sections. The second section provides an overview of the CRITIC methodology with a detailed description of the newly extended EDAS-M approach. The third section is dedicated to the numerical verification of the proposed method, providing a detailed description of all calculations, with each step being addressed separately. The fourth section conducts a sensitivity analysis, comparing the proposed approach When examining the impact of dynamic matrix compared to other MCDM techniques rank variations. [20] In particular, existing MCDM methods, including the EDAS method, focus only on ranking the available alternatives, without accounting for situations where one or more alternatives are rejected, accepted, or newly introduced. Once the ranking is complete, the process must be restarted from the beginning to add new options. Similarly, if one or more alternatives are removed, the ranking must be recalculated. This limitation is a common shortcoming of current MCDM methods. To address this issue, this research is a solution to improve the adaptive capacity of the ranking process. [21] They also emphasize that the main objective of the goal of an organization is to identify employees who will not only excel in their work but also experience job satisfaction. Considering the importance of human resources within an organization, the recruitment and selection process is an important aspect of HRM activities. Recruitment involves attracting a sufficient number of qualified candidates, which helps the organization select the best fit for the vacant positions.

On the contrary, selection involves selecting the best candidates from a pre-screened pool of applicants. [22] The proposed approach offers several advantages. Current fuzzy extensions of EDAS methods often impose constraints on decision makers when expressing preferences for alternatives. In particular, they must be assigned membership, non-sum of the membership and non-membership degrees cannot exceed one. For example, IVIF-EDAS, a variant of fuzzy EDAS, imposes a constraint on decision makers by requiring the sum of the upper bounds of membership and non-membership degrees is exactly one. [23] MCDM techniques provide a useful means of identifying the strengths and weaknesses of a particular online course. Researchers have developed various models to assess e-learning quality and rank e-learning platforms. This study examines Application of the EDAS method to evaluate e-learning courses, using seven criteria derived from the perspectives of twenty-four respondents. The primary motivation for choosing the EDAS method was its ease of use and relevance for decision-making. [24] The EDAS method, originally designed for inventory classification problems, has been validated for use in MCDM situations. This approach

evaluates alternatives in an MCDM problem by determining their positive and negative deviations from the mean solution. In this approach, an alternative is considered most favorable if it has a significant positive deviation and a minimal negative deviation from the mean solution. The implementation of the EDAS method follows the following steps: [25] The proposed EDAS algorithms are particularly useful when combining absolute L1 measures, such as Manhattan, Gower, or Lorentzian distances, to evaluate alternatives with comparable mean values. Conversely, modifications that use normalized distances, such as Sorensen, Serge, Kaczynski, or Canberra distances, are more appropriate when estimates vary significantly. The reliability of the proposed MCDM approach is strengthened when results are consistent across different distance measures. As a result, these algorithms extend the MCDM toolkit to accommodate both precise and uncertain values, improving decision justification in a variety of practical applications. [26] However, the problem becomes more complex due to uncertainty, making the decision-making process more difficult.

To address quality criteria in material selection, decision makers have used fuzzy logic. Kababs et al. implemented a simplified fuzzy logic approach to evaluate material quality properties. The effectiveness of this method was demonstrated through material selection cases including a liquid nitrogen storage tank, an aircraft wing spar, and a sailboat mast. [27] A fuzzy programming approach is used to solve this multi-objective model. In addition, a sensitivity analysis is performed to assess how changes in environmental criterion weights affect the total purchasing costs and order quantities from each supplier. The results suggest that the proposed integrated model is well suited for real-world applications. The remainder of this paper is organized as follows: The next section provides a brief literature review on supplier evaluation with environmental considerations, supplier selection and order allocation, and the application of IT2FSs in MCDM problems. [28] Switching to electric motorcycles can contribute to reducing dependence on fossil fuels; however, its overall impact depends on the energy production methods and the speed of adoption. A fuzzy programming approach is used to solve this multi-objective model, and a sensitivity analysis is conducted to examine how variations in environmental criterion weights affect total

procurement costs and order quantities from each supplier.

The remainder of this paper is structured as follows: The next section provides a brief literature review on supplier evaluation with environmental considerations, supplier selection and order allocation, and the application of IT2FSs in MCDM problems will be affected by energy production methods and the pace of vehicle replacement. [29] Murshidabad district is located in the central part of West Bengal. India is undergoing significant agricultural expansion. Since groundwater stress in this area has not been extensively studied, specific parameters were selected for a detailed assessment of the groundwater stress zone. The primary purpose of this study aims to investigate the spatial distribution of areas susceptible to groundwater stress and determine their percentage prevalence. These findings will serve as valuable information for future planning, helping policy makers, local authorities and planners in ensuring sustainable management of groundwater resources. [30]

3. PROPOSED SYSTEM

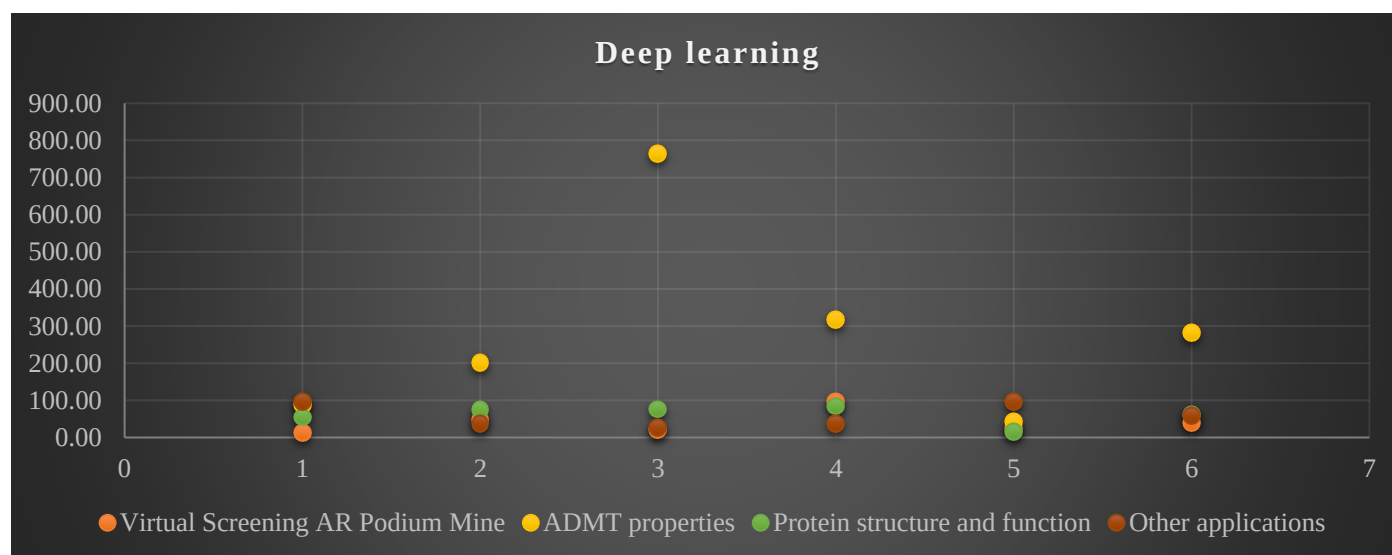
Table 1 compares various deep learning models using the EDAS method in several applications, including virtual screening, ADMET properties, protein structure and function, and other areas. The recurrent neural network (RNN) achieves the highest score in virtual screening (97.00), while the deep autoencoder network stands out in ADMET properties (763.00). The deep feed-forward network performs best in protein structure and function (95.00), while the layered neural network ranks highest in other applications (96.00). The average values (AVj) highlight the overall trend, with ADMET properties having the highest average (281.80), underscoring its importance in deep learning. Figure 1 illustrates the performance of various deep learning models evaluated using the EDAS method various domains. The deep autoencoder network shows the best performance in ADMET properties (763.00), while the continuous neural network achieves the highest score in virtual screening (97.00). The deep feed-forward network excels in protein structure and function (95.00), highlighting the unique strengths of each model.

Table 1. Deep learning

	Virtual Screening AR Podium Mine	ADMT properties	Protein structure and function	Other applications
Deep feed-forward network	12.00	88.00	54.00	95.00
Deeply controlled Boltzmann machine	47.00	200.00	75.00	37.00
Deep automatic encoder network	21.00	763.00	76.00	26.00
Recurrent neural network	97.00	316.00	84.00	37.00
Layered neural network	25.00	42.00	15.00	96.00
AVj	40.40000	281.80000	60.80000	58.20000

Table 2. Positive distance average (PDA)

	Positive Distance from Average (PDA)			
Deep feed-forward network	0.00	0.00	0.11	0.00
Deeply controlled Boltzmann machine	0.16	0.00	0.00	0.36
Deep automatic encoder network	0.00	1.71	0.00	0.55
Recurrent neural network	1.40	0.12	0.00	0.36
Layered neural network	0.00	0.00	0.75	0.00

**Fig. 1.** Deep learning**Table 3.** Negative distance from average (NDA)

	Negative Distance from Average (NDA)			
Deep feed-forward network	0.70297	0.68772	0.00000	0.63230
Deeply controlled Boltzmann machine	0.00000	0.29028	0.23355	0.00000
Deep automatic encoder network	0.48020	0.00000	0.25000	0.00000
Recurrent neural network	0.00000	0.00000	0.38158	0.00000
Layered neural network	0.38119	0.85096	0.00000	0.64948

Table 2 presents the average positive distance (PDA) values for different deep learning models using the EDAS method. The continuous neural network records the highest PDA in virtual screening (1.40), which shows a significant deviation from the mean. The deep autoencoder network excels in ADMET properties (1.71), while the layered neural network demonstrates significant PDA in protein structure and function (0.75). The deep constrained Boltzmann machine achieves the highest PDA in other applications (0.36). These differences highlight the unique strengths of each model in specific domains, emphasizing their specialized capabilities within deep learning applications.

Table 3 provides a summary of the negative distance from the mean (NDA) values for different deep learning

models are given using the EDAS method. The deep feed-forward network shows the highest NDA in virtual screening (0.70297) and ADMET properties (0.68772), indicating low performance compared to the average. The layered neural network also shows significant NDA values in ADMET properties (0.85096) and other applications (0.64948). The continuous neural network records an NDA of 0.38158 in protein structure and function, while the deep restricted Boltzmann machine and the deep autoencoder network show varying performance in different categories. These values highlight the performance disparities between the models.

Table 4 presents the weight values assigned to various deep learning models using the EDAS method. Each model, including the deep feed-forward network, the deep

supervised Boltzmann machine, the deep autoencoder network, the continuous neural network, and the layered neural network, is weighted uniformly at 0.75 across all categories. This equal distribution ensures that no model is favored over another, which promotes fair evaluation. The consistency in weighting indicates that performance differences arise from the intrinsic capabilities of the models rather than external biases, which helps to objectively compare their performance across different applications.

Table 5 Shows Weighted positive distance average (PDA) and Spi values for various deep learning models are presented using the EDAS method. The deep autoencoder network achieves the highest Spi value (1.69564), largely due to its strong performance in ADMET properties (1.28070) and other applications (0.41495). The continuous neural network is in second place with a Spi of 1.41496, excelling in virtual screening (1.05074). The deep supervised Boltzmann machine also performs well, recording a Spi of

0.39572. In contrast, the layered neural network and the deep feed-forward network have low Spi values, reflecting their relatively weak contributions towards categories.

Table 6 presents the weighted negative distance average (NDA) and SNi values for various deep learning models using the EDAS method. The deep feed-forward network records the highest SNi value (1.51725), which reflects the largest deviation below the mean, especially in virtual screening (0.52723) and ADMET properties (0.51579). The layered neural network follows closely with an SNi of 1.41122, showing significant deviations in ADMET properties (0.63822) and other applications (0.48711). On the contrary, the deep restricted Boltzmann machine (0.39287) and the continuous neural network (0.28618) exhibit lower SNi values, indicating a strong alignment with the mean across various application domains.

Table 4. Weight

	Weight			
Deep feed-forward network	0.75	0.75	0.75	0.75
Deeply controlled Boltzmann machine	0.75	0.75	0.75	0.75
Deep automatic encoder network	0.75	0.75	0.75	0.75
Recurrent neural network	0.75	0.75	0.75	0.75
Layered neural network	0.75	0.75	0.75	0.75

Table 5. Weighted PDA, Spi

	Weighted PDA				Spi
Deep feed-forward network	0.00000	0.00000	0.08388	0.00000	0.08388
Deeply controlled Boltzmann machine	0.12252	0.00000	0.00000	0.27320	0.39572
Deep automatic encoder network	0.00000	1.28070	0.00000	0.41495	1.69564
Recurrent neural network	1.05074	0.09102	0.00000	0.27320	1.41496
Layered neural network	0.00000	0.00000	0.56497	0.00000	0.56497

Table 6. Weighted NDA, SNi

	Weighted NDA				SNi
Deep feed-forward network	0.52723	0.51579	0.00000	0.47423	1.51725
Deeply controlled Boltzmann machine	0.00000	0.21771	0.17516	0.00000	0.39287
Deep automatic encoder network	0.36015	0.00000	0.18750	0.00000	0.54765
Recurrent neural network	0.00000	0.00000	0.28618	0.00000	0.28618
Layered neural network	0.28589	0.63822	0.00000	0.48711	1.41122

Table 7. NSPi, NSNi, ASi, Rank

	NSPi	NSNi	ASi	Rank
Deep feed-forward network	0.04947	0.00000	0.02473	5
Deeply controlled Boltzmann machine	0.23337	0.74106	0.48722	3
Deep automatic encoder network	1.00000	0.63905	0.81953	2
Recurrent neural network	0.83447	0.81138	0.82292	1
Layered neural network	0.33319	0.06988	0.20153	4

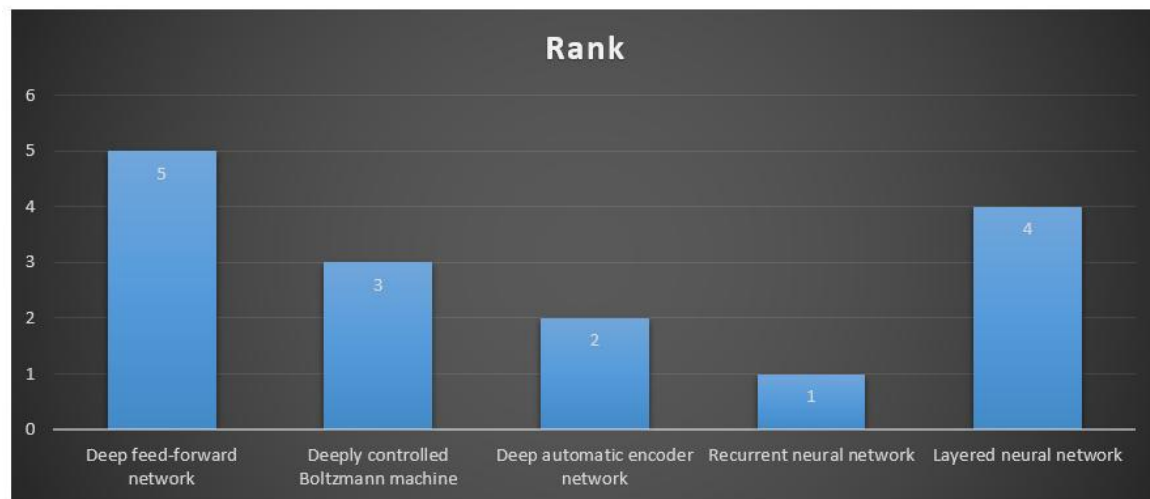
**Figure 2.** Rank

Table 7 presents the NSPi, NSNi, ASI values and rankings of various deep learning models using the EDAS method. The recurrent neural network (RNN) maintains the highest ASI value (0.82292), holding the first position and showing strong overall performance. The deep autoencoder network closely follows with an ASI of 0.81953, holding the second position. The deep supervised Boltzmann machine holds the third position (0.48722), while the layered neural network holds the fourth position (0.20153). The deep feed-forward network is in last place, with the lowest ASI (0.02473), indicating relatively weak performance. These rankings emphasize the relative strengths and limitations of each model in different applications.

Figure 2 illustrates the ranking of deep learning models based on the EDAS method. The recurrent neural network (RNN) takes the top spot, showing the overall performance. The deep autoencoder network is in second place, while the deep supervised Boltzmann machine is in third place. The layered neural network and the deep feed-forward network occupy the fourth and fifth places, respectively.

5. CONCLUSION

The integration of deep learning with Multi-objective

decision making (MCDM) techniques, especially the EDAS approach, play a key role in addressing complex evaluation problems a significant advance in tackling complex decision-making challenges in various fields. This review highlights key insights, emphasizing how deep learning's ability to process vast data through multiple neural network layers has revolutionized traditional data analysis in areas such as healthcare, ophthalmology, remote sensing, and drug discovery, with profound progress learning architectures, including deep feed-forward networks, Boltzmann machines, auto encoders, and recurrent neural networks, has enabled sophisticated data modeling. Meanwhile, MCDM methods, especially EDAS, effectively evaluate alternatives in uncertain environments, finding applications in battery technology, agriculture, and e-learning. The literature identifies a number of challenges that persist in both deep Machine learning and multi-criteria decision analysis (MCDM) methods. Deep learning faces issues such as handling increasingly complex data, ensuring privacy for sensitive user information, and improving pre-processing techniques. On the other hand, MCDM methods face the need to restart evaluations when alternatives change and limitations in preference expression within fuzzy extensions. Recent research has addressed these challenges through innovations such as transfer learning, Bayesian optimization, and modifications of the EDAS method that include various

distance metrics. Future efforts should focus on integrating deep learning with MCDM to improve adaptability, computational efficiency, and user-friendliness of decision support systems. Strengthening uncertainty management and refinement interfaces will further improve decision-making in fields such as healthcare, drug development, environmental management, and human resources. By combining the pattern recognition strengths of deep learning with the structured evaluation frameworks of MCDM, more effective and informed decisions can be made in increasingly complex, data-rich environments.

DECLARATIONS

Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

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All of the data obtained or analyzed during this study is included in the report that was submitted.

Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

Authors' contributions

All authors contributed equally in the preparation of this manuscript.

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