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Review

Deep Learning and Neural Networks: Decision-Making Implications

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Abstract: Deep learning techniques have found applications across diverse fields, enhancing the efficiency and effectiveness of decision-making processes. The integration of these techniques underscores the significance of interdisciplinary research. In particular, decisions often rely on the output's projected value or probability from neural networks, considering different values of the relevant output factor. This interdisciplinary review examines the impact of deep learning on decision-making systems, analyzing 25 relevant papers published between 2017 and 2022. The review highlights improved accuracy but emphasizes the need for addressing issues like interpretability, generalizability, and integration to build reliable decision support systems. Future research directions include transparency, explainability, and real-world validation, underscoring the importance of interdisciplinary collaboration for successful implementation.

Keywords: decision making; deep learning techniques; neural networks; symmetry; interpretability; collaboration; trustworthiness

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1. Introduction

Neuroscientists have long described the characteristics and operations of the nervous system, and they are becoming more successful in explaining how the brain carries out the functions it does [1]. However, identifying optimal behaviors in the actual world can be challenging due to the complexity of the environment and social dynamics [2]. Numerous neurological and psychiatric disorders exacerbate the involvement of multiple brain regions and circuits in this decision-making process [3]. Traditional approaches have dominated optimal behavior research. Among these, a prescriptive strategy addresses the question of which solution is optimal for a given problem. Game theorists and economists, for instance, characterize how self-interested rationales need to behave individually or collectively [4]. These traditional approaches have recently merged with neuroscientific theories, wherein learning plays a crucial role in selecting optimal behaviors and decisions. Specifically, the reinforcement learning (RL) theory provides a useful framework for modeling how an individual's behaviors are modified through experience [5,6]. Neuroscientists have begun to identify numerous fundamental brain mechanisms responsible for various decision-making processes and computational learning. Their findings now appear frequently in the scholarly literature of numerous disciplines, including financial and economic decisions [7], marketing [8], ethics [9], etc.

Decision-making has been a central topic in organization studies for decades [10]. The concept of symmetric decision making refers to the equilibrium and symmetry of the decision-making process and its outcomes. By considering a variety of factors, perspectives, and options and ensuring consistency, fairness, and transparency, symmetric decision-making is possible [11]. Utilizing the appropriate techniques and technologies, such as deep learning and neural networks, can enhance the accuracy, efficacy, and interpretability of the decision-making process [12–14].

Scholars have pondered how organizational technology, structures, and processes facilitate or restrict decision-making and influence decision-making outputs [15]. Developments in deep learning algorithms—a subset of machine learning algorithms largely inspired by the cognitive system's ability to observe, analyze, learn, and make decisions about complex problems through abstraction and a hierarchical approach—have accelerated the incorporation of artificial intelligence (AI) into organizational decision making, according to early observations [16]. Many of the issues that professionals and researchers are trying to solve seem to have potential solutions in AI [17]. Deep learning-augmented decision making refers to the decision-making process in organizations (including operations, finance, marketing, human resources, and strategy) that is augmented with deep learning algorithm outcomes.

Although it is beneficial for researchers to dissect neuropsychologically interpretable variables, these analyses provide only extremely limited predictive guidelines and are incapable of modeling more complex real-world decision-making scenarios, such as social dilemmas [18]. In the past decade, deep learning techniques based on neural networks have garnered significant interest from academia and industry. Deep neural networks have achieved tremendous success in various application domains, including Recommender Systems [19], natural language processing (NLP) [20], and Computational Vision [21]. Deep neural networks are significantly more expressive and adaptable to complex data input than traditional machine learning models.

Deep learning as a foundation for modeling brain function has recently attracted much attention [22–24]. Deep learning has been studied for modeling numerous systems, including cognitive control [25], navigation [26], motor control [27], audition [28], and vision [29]. Recent advancements in AI and machine learning have sparked a resurgence of interest in deep learning. Progress in employing explicit "correct answers" during training to train deep learning systems for tasks like image classification [30,31] is particularly pertinent.

Deep learning-augmented decision making has spread quickly throughout other enterprises, not just huge technology companies [32]. Businesses across various sectors, including banking, insurance, retail, transportation, energy, and healthcare, use deep learning-augmented decision making to enhance organizational performance. This review aims to discuss the importance of the connection between neural networks and decision making and explore how deep learning approaches have enhanced decision making by reviewing the articles published in the past five years. It addresses the following research questions (RQs):

I. RQ1: What are the decision-making implications of deep learning and neural networks?
II. RQ2: How can deep learning and neural networks be used in decision support systems?
III. RQ3: What are future directions and research opportunities of deep learning and neural networks for decision-making implications?

2. Overview of Deep Learning and Neural Networks

2.1. Key Concepts

Deep neural networks are computational systems comprising units that resemble neurons and are connected through synapse-like connections. These units transmit scalar values akin to spike rates, which are determined by the total of their inputs or the activity of preceding units multiplied by the strength of the transmitting synapse, as explained by Goodfellow et al. [13]. It is noteworthy that the activity of these units is governed by non-linear functions applied to their inputs. This non-linearity enables the creation of networks with multiple layers of units positioned between the "output" and "input" sides, giving rise to what we call "deep" neural networks. These deep networks have the capacity to approximate any function that maps activation inputs to activation outputs [33]. Additionally, there are "recurrent" neural networks (RNNs) that can compute functions based on input sequences, as their network activations can retain information from previous events when loops are present in the connection topology [34].

The term "deep learning" encompasses the challenge of adjusting the link weights within a deep neural network to achieve a desired input–output mapping [35]. However, while backpropagation has been in use for over three decades, it was primarily applied to supervised and unsupervised learning scenarios. In supervised learning, the objective is to learn from labeled data, whereas in unsupervised learning, the focus is on creating meaningful representations of input data. These paradigms are quite distinct from reinforcement learning (RL), where the learner must determine actions that maximize rewards. RL also introduces the concept of exploration, where the learner must balance the search for new actions with exploiting previously acquired knowledge. Unlike traditional supervised and unsupervised learning, RL assumes that the actions taken by the learning system influence its future inputs, creating a sensory–motor feedback loop. This introduces complexities due to non-stationarity in the training data, and the desired outcomes in RL often involve multiple decision-making steps rather than simple input–output mappings [36].

One of the formidable challenges faced by scholars and professionals is making decisions based on massive data while considering multiple criteria. Researchers are actively exploring innovative approaches to build decision support systems that integrate AI and machine learning to address the diverse challenges across various big data application domains. These systems facilitate decision making by taking into account a range of factors such as the number of options, effectiveness, and potential outcomes. There exist several decision support systems designed to assist in this complex decision-making process [37,38]. Effective decision making is paramount for the success of businesses and organizations, given the multitude of criteria that can influence whether or not a particular course of action should be pursued [39].

The integration of deep learning algorithms into current approaches for handling large datasets has enabled the development of more intelligent decision support systems [40,41]. These systems find applications in various industries, including agriculture, the energy sector, and business [42–44]. Multiple disciplines offer a range of theories and techniques, from fundamental to advanced and intelligent models, to aid in the decision-making process [45,46].

2.2. Preprocessing Stages and Caveats in AI Decision Making

The preprocessing of data is a pivotal step in the decision-making process for AI models. Raw data must undergo cleansing, transformation, and engineering to make it suitable for analysis and model training. Data cleansing involves handling issues like missing values and outliers to prevent skewed results. However, mismanagement at this stage can introduce errors and alter the behavior of the model [47]. Integrating data from various sources presents challenges due to diverse formats, dimensions, and units. Care must be taken to avoid conflicts and errors in this process [48]. Additionally, the selection of relevant features and the creation of new ones based on domain expertise can enhance model performance. Nevertheless, incorrect decisions may lead to overfitting or the loss of critical information [49].

Different data types, such as sequential or text data, come with specific constraints. When dealing with sequential data, maintaining the order of samples is crucial to avoid inaccurate predictions or the loss of temporal trends [48]. In the interim, tokenization, stemming, and stop word elimination are required for text data preprocessing; however, improper control of these processes can result in the loss of crucial context or meaning [47]. To avoid introducing majority-class bias, it is also necessary to evaluate how to manage data imbalances in classification assignments [49]. To protect user privacy, the personal information in the dataset needs to be anonymized or encrypted. Equal weight is given to privacy and security considerations [48].

Data scientists need to establish a balance between model complexity and interpretability to develop a robust and trustworthy model. Some preprocessing techniques may increase precision but also reduce interpretability, which can be problematic when making crucial decisions [49]. Additionally, since preprocessing should not result in extensive data fitting, the model's generalizability should be maintained [47]. To evaluate the effects of each preprocessing stage and determine the most appropriate techniques for the task, a comprehensive understanding of the data, domain, and issue at hand is required [48]. Regular validation and testing of the model using diverse preprocessing techniques facilitate selecting the most effective AI-driven decision-making procedures [47,49].

2.3. Types of Neural Networks Used in Decision Making

Neural networks represent a powerful class of machine learning algorithms that have found widespread application in decision-making tasks [50]. They are designed to learn and simulate complex interactions between inputs and outputs, drawing inspiration from the functioning of the human brain. Neural networks typically consist of interconnected neurons organized into layers, with the three primary layer types being the input, hidden, and output layers [51]. Each neuron receives input, performs mathematical processing, and produces an output, which is then transmitted to neurons in subsequent layers.

The primary strength of neural networks lies in their ability to learn from and generalize across extensive datasets. During the training phase, the network adjusts its internal parameters, known as weights, based on input–output examples. The objective is to minimize the disparity between the actual outputs in the training data and the network's predictions. Once trained, neural networks can be deployed for decision-making tasks by providing new data as the input and obtaining predictions as the output. Through training, neural networks acquire the capability to identify patterns and make inferences, making them suitable for applications such as classification, regression, and pattern recognition.

Different neural network architectures are employed in decision-making scenarios [52–55]. The feedforward neural network (FNN) represents one of the most fundamental types, where data flow from the input layer to the output layer in a unidirectional manner [56]. Convolutional neural networks (CNNs) are commonly used for image and video analysis, as they can capture spatial correlations through convolutional layers [57,58]. RNNs are well-suited for tasks involving sequential data due to their cyclic connections, allowing them to model temporal dependencies [34].

Neural networks have found successful applications in various decision-making domains, including natural language processing (NLP), computer vision, speech recognition, recommendation systems, and autonomous vehicles. Their ability to recognize intricate patterns and make precise predictions has made them invaluable tools across numerous industries. However, neural networks also face challenges, such as computational complexity, extensive training time, and the risk of overfitting, where the network memorizes training data rather than generalizing effectively to new data. To address these issues, regularization techniques and appropriate data preprocessing are commonly employed.

Neural networks are a potent class of machine learning algorithms applied to decision-making problems. They learn from data to create predictions or conclusions based on intricate patterns and relationships. They have become a key tool in AI due to their adaptability and capacity for handling complex issues. Neural networks come in a variety of forms and are utilized frequently in numerous industries. Classification, regression, and pattern recognition applications utilize the most fundamental FNN or multilayer perceptron type [59]. CNNs are the best choice for image-related tasks such as classification, object detection, and segmentation because they are so adept at interpreting visual input [60]. Recurrent neural networks (RNNs) are well-suited for sequential data, such as time series or NLP, due to their cyclic connections, which permit the modeling of temporal dependencies [61]. Variants such as Long Short-Term Memory (LSTM) [62] and Gated Recurrent Unit (GRU) [63] enable RNNs to better manage long-term dependencies, thereby resolving the problem of vanishing gradients [64].

Furthermore, Generative Adversarial Networks (GANs) introduce a unique approach where discriminator and generator networks compete to create increasingly realistic synthetic data. GANs have demonstrated success in tasks such as unsupervised learning, data synthesis, and image generation [65]. Additionally, reinforcement learning (RL) networks combine neural networks with RL algorithms to facilitate learning through interaction with the environment, making them suitable for decision-making tasks with delayed rewards, such as gaming, robotics control, and autonomous systems [66].

The selection of the most appropriate deep learning technique depends on factors like the type of data, task requirements, and the need to identify specific dependencies or patterns (Figure 1). Researchers and practitioners continually experiment with various neural network topologies to push the boundaries of AI and decision making, seeking optimal solutions for their unique use cases.

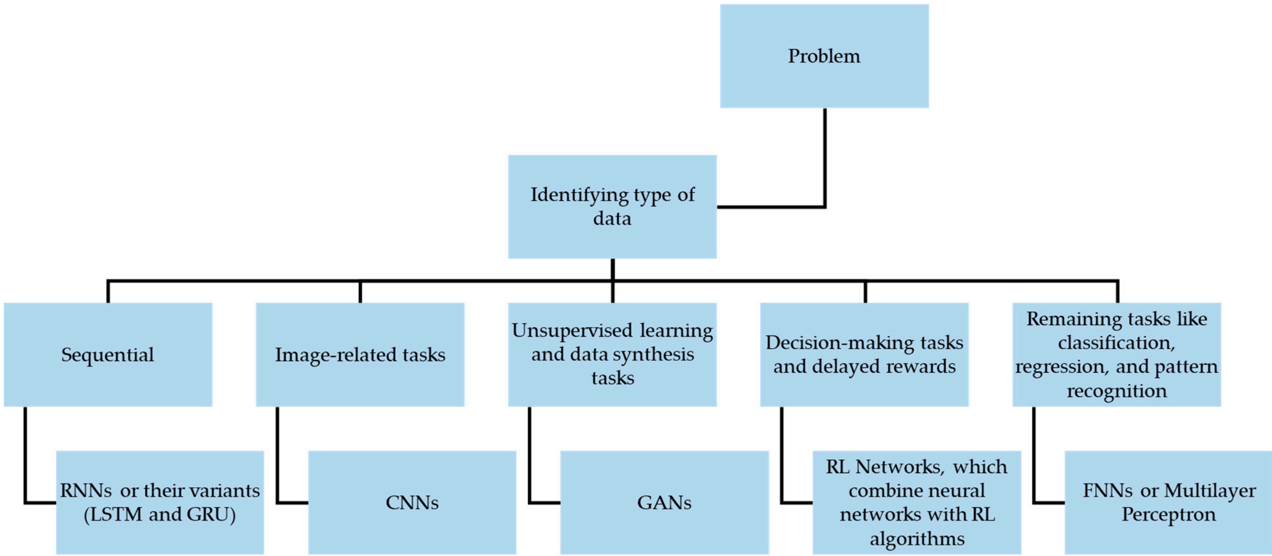

Figure 1. Selecting the right neural network for the problem domain.

A few types of neural networks applied to decision-making problems are listed in Figure 1. In addition to the previously mentioned neural network architectures, several other specialized models are applied to decision-making problems, including transformer networks, deep belief networks, and self-organizing maps. These architectures each have their own unique strengths and are suitable for specific types of data and tasks. The choice of the most appropriate neural network architecture depends on the nature of the data being processed and the problem at hand. Figure 2 provides a high-level overview of the neural network decision-making process, from the initial choice of network type to the generation and presentation of the final decision or prediction. The provided flowchart can be adjusted and customized to suit the specific decision-making task at hand. Due to their adaptable nature, neural network configurations can effectively serve a wide range of decision-making scenarios.

2.4. Deep Learning Algorithms and Architectures

A subset of machine learning techniques based on learning data representations is known as deep learning. The fundamental component of deep learning neural networks is the distributed information processing and communication nodes seen in biological systems. Convolution neural networks, multilayer perceptrons, restricted Boltzmann machines (RBMs), auto-encoders, RBMs, RNN, and others are some of the different components of deep learning [67–69]. A feed-forward neural network with many hidden layers is called a multilayer perceptron with an autoencoder. Perceptrons that use arbitrary activation functions are included in each layer. An unsupervised learning model called an auto-encoder aims to recreate the input data in the output. The backpropagation approach used by this neural network determines the gradient of the error function about the neural network's weights. The primary component of learning representation encodes the input and reduces large vectors into small vectors. The tiny vectors record the most important vector characteristics that aid in data compression, dimensionality reduction, and data reconstruction. Convolution layers make up the feed-forward neural network known as the CNN. These convolution layers capture the local and global feature that contributes to improving accuracy. Hidden and visible layers are parts of the two-layer neural network that makes up the RBM. There is no interlayer communication between the visible and the concealed layers. This RBM extracts features and attributes using the gradient descent approximation approach. Figure 3 depicts deep learning's components (neural networks: multilayer perceptron with auto-encoder, CNN, and RBM), and learning representation.

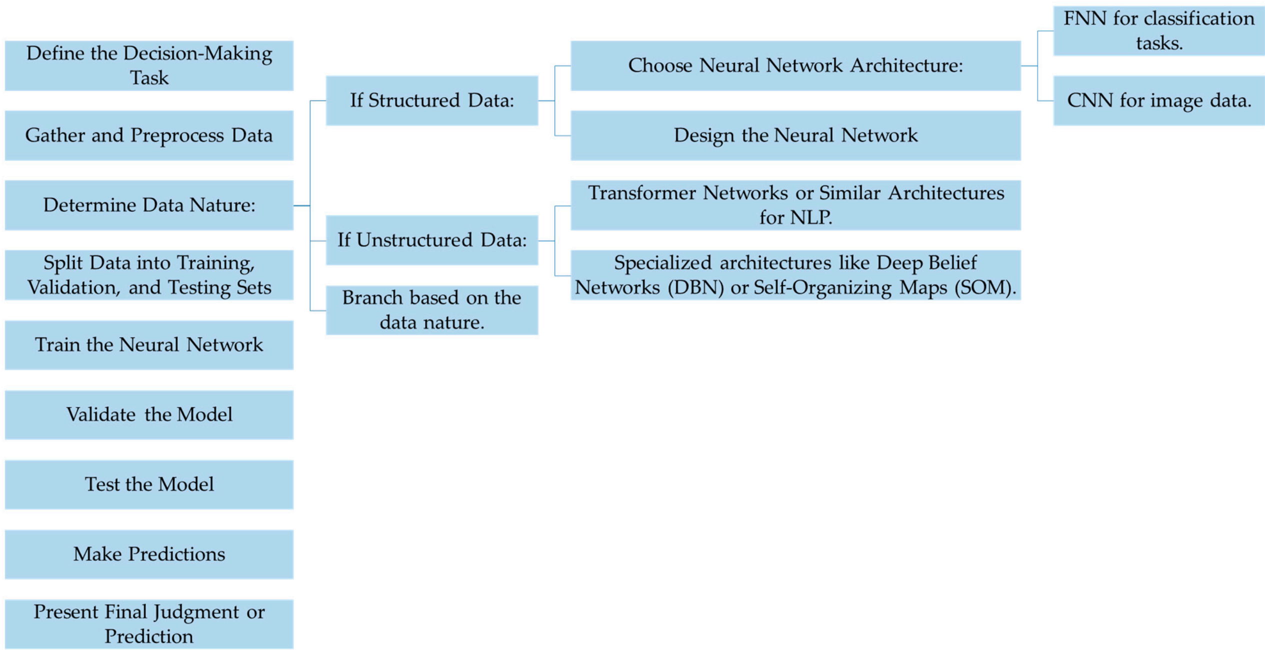

Figure 2. Neural networks in decision-making process flowchart.

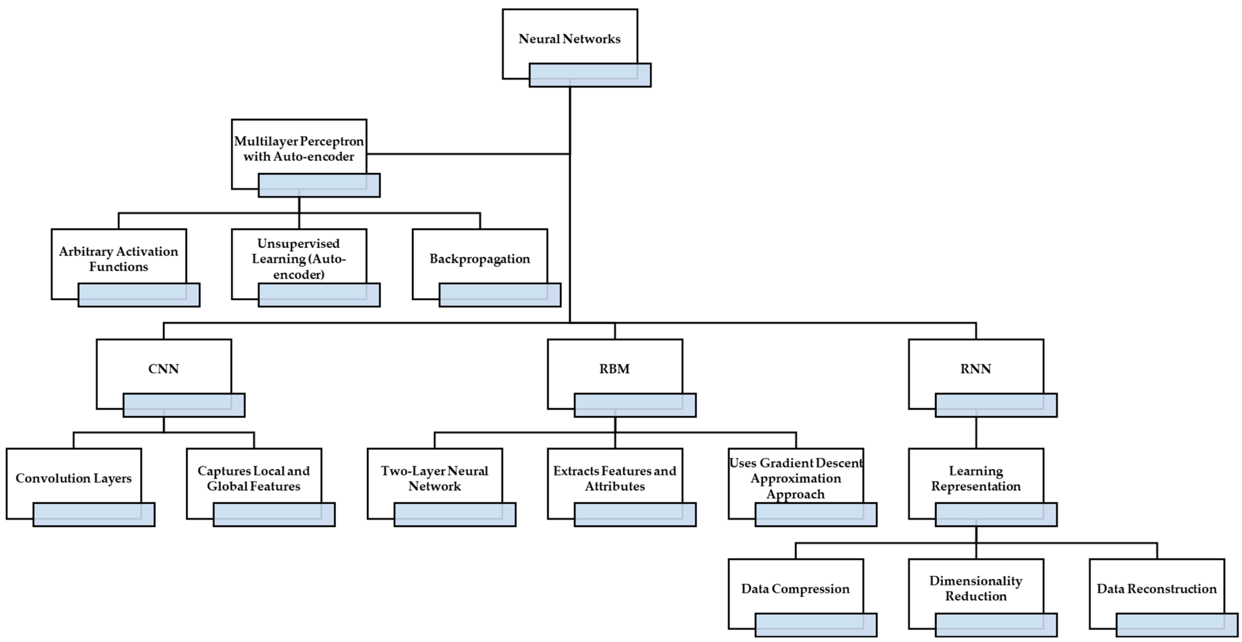

Figure 3. Deep learning methods and their practical applications.

Over the past decade, managers have rapidly adopted deep learning to enhance decision making across various levels and processes within organizations [70]. Deep learning applications within companies have seen significant utilization in the context of the ever-expanding realm of social media activities, which generate vast amounts of user-generated content [71]. Much of this content is in unstructured formats, including text, photos, and videos. Deep learning algorithms have been instrumental in navigating and extracting insights from this complex digital landscape, often referred to as the "echoverse". This echoverse encompasses not only user-generated content but also includes content generated by organizations themselves, traditional news media, and press releases [72]. Deep learning technologies have proven invaluable in processing and making sense of the rich and diverse data within this echoverse, thereby enhancing decision-making capabilities for businesses.

2.5. Applications of Deep Learning and Neural Networks in Decision Making

Deep learning and neural networks have revolutionized various fields by harnessing their capability to process vast datasets and discern meaningful patterns [73]. In computer vision, they have ushered in a transformative era, reshaping tasks such as object detection, facial recognition, and image categorization [74]. These neural networks are now being trained on extensive datasets to make precise decisions based on visual information, enabling innovations like autonomous vehicles, surveillance systems, and medical image analysis [30]. Their adeptness at identifying and classifying objects in images has led to advancements in domains as diverse as agriculture and healthcare [75].

In the realm of natural language processing (NLP), deep learning has achieved remarkable progress, with neural networks excelling in various applications, including language translation, sentiment analysis, and question-answering systems [76–78]. They make it possible for chatbots, virtual assistants, and search engines to comprehend language since they can evaluate and interpret textual content [79]. These innovations have fundamentally improved human–computer interfaces and transformed how humans interact with technology [75,76].

Recommender systems have also benefited significantly from deep learning techniques, as neural networks can deliver personalized recommendations in e-commerce platforms, streaming services, and social media by analyzing user preferences and historical data [80]. Consequently, user experiences have been enhanced, engagement has soared, and content delivery has become more efficient [81].

Furthermore, the influence of deep learning extends into the realm of financial decision making, where neural networks have made a substantial impact by evaluating intricate financial data, predicting stock market trends, detecting fraud, and supporting algorithmic trading and credit scoring [82]. These models empower real-time decision making by scrutinizing vast datasets and uncovering trends, thereby mitigating risk and enhancing financial performance [83]. In summary, the versatile applications of deep learning and neural networks span multiple domains, including computer vision, NLP, recommender systems, and financial decision making, as highlighted in Table 1. These technologies have ushered in transformative changes by harnessing their data-processing prowess to extract valuable insights and drive innovation.

Table 1. Overview of the various applications of deep learning and neural networks in decision making across different fields.

Application	Description	Technical Aspect
Image and Object Recognition	Deep learning models for image classification, object detection, and facial recognition.	CNNs and Transfer Learning
NLP	Neural networks for language translation, sentiment analysis, and question-answering systems.	RNNs, Transformers, and Word Embeddings

Table 1. *Cont.*

Application	Description	Technical Aspect
Recommender Systems	Personalized recommendations in e-commerce, streaming services, and social media platforms.	Collaborative Filtering and Matrix Factorization
Financial Decision Making	Stock market prediction, fraud detection, credit scoring, and algorithmic trading.	Time Series Analysis and Reinforcement Learning
Healthcare and Medicine	Medical diagnosis, disease prediction, and treatment planning using medical data and images.	Medical Imaging Analysis and Clinical Data Integration
Autonomous Systems	Decision making in self-driving cars, drones, and robots for navigation and task execution.	Sensor Fusion and Path Planning
Anomaly Detection	Identifying anomalies or outliers in network security, fraud detection, and predictive maintenance.	Autoencoders and Isolation Forests
Gaming and Strategy	Deep learning models trained through RL for game playing and strategy.	RL and Deep Q-Networks (DQN)

3. Methodology

The research methodology follows the PRISMA guidelines for systematic reviews and involves three main databases: ScienceDirect, Google Scholar, and Web of Science. A total of 202 pertinent papers published between 2017 and 2022 were initially retrieved from these sources. After eliminating duplicates, 182 unique articles remained. Subsequently, the titles and abstracts of these articles were screened and 30 relevant papers were identified for further consideration.

In the next phase, the full texts of the 30 selected articles were assessed for eligibility, excluding review papers and book chapters. As a result, 25 articles were included in the final review. The entire systematic review process was completed on 18 May 2023. The selected databases, ScienceDirect, Google Scholar, and Web of Science, were essential tools in the comprehensive literature search, ensuring a rigorous and transparent approach to conducting the review. The PRISMA guidelines provided a standardized methodology to reduce bias and present a well-rounded perspective on the research topic. The processes for building a research database based on the PRISMA paradigm are shown in Figure 4.

The above-described research methodology has a number of limitations. One concern is the reliance on particular databases such as ScienceDirect, Google Scholar, and Web of Science, which may introduce publication and language biases, resulting in the omission of relevant studies published in lesser-known sources and different languages. In addition, the time limit of considering only articles published between 2017 and 2022 may cause researchers to neglect recent findings. In addition, the selected databases may not include all the pertinent literature, and the screening procedure based solely on the title and abstract may exclude valuable papers. Another limitation is the subjectivity of the eligibility criteria used during the full-text evaluation, which may have an impact on the overall scope and quality of the review.

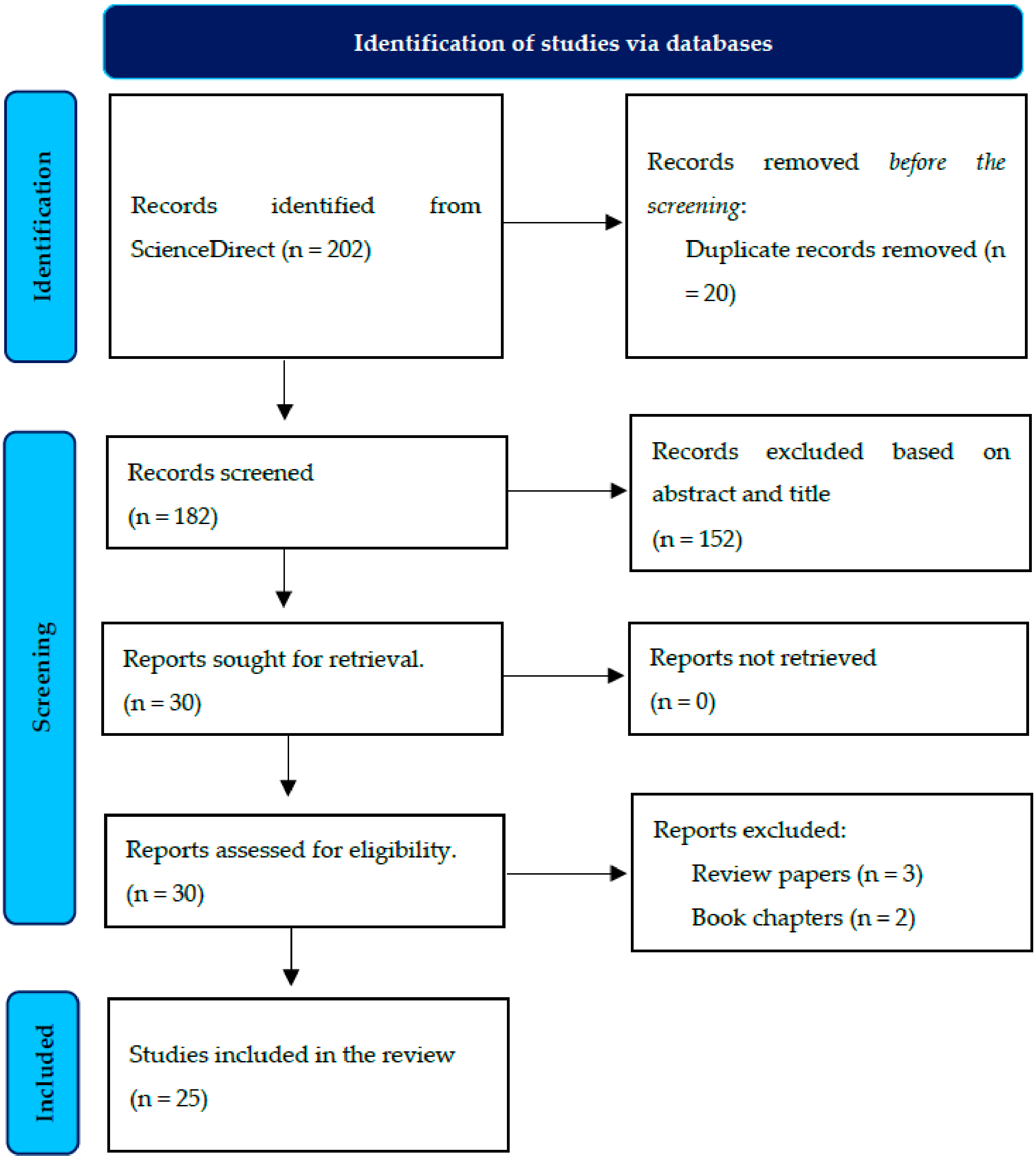

Figure 4. PRISMA flowchart showing the selection process.

4. Results

This systematic review aims to investigate the decision-making implications of deep learning and neural networks. This review conducted a comprehensive search of the relevant literature and identified a total of 25 articles that met the inclusion and exclusion criteria.

4.1. Subject Area

The articles included in the systematic review covered a wide range of subject areas, reflecting the diverse applications of deep learning and neural networks in decision making. The distribution of articles across different subject areas is summarized in Table 2. The most common subject area represented in the included articles was Computer Science, with 14 articles. This is not surprising, as deep learning and neural networks are foundational techniques within the field of computer science and are widely studied and applied in various subdomains such as machine learning, AI, and data science. Additionally, 6 articles explored the implications of deep learning in other subject areas such as Decision Sciences, Engineering, Medicine, and Dentistry. Deep learning has gained significant attention in decision sciences due to its ability to extract complex patterns and make predictions based on large and complex datasets. Furthermore, 8 articles were dedicated to the field of Business, Management, and Accounting. Deep learning techniques have increasingly been utilized in business-related domains for tasks such as customer behavior analysis, fraud detection, financial forecasting, and market prediction. The ability of deep learning models to process and analyze vast amounts of data has made them valuable tools for decision making in these areas. The remaining articles covered various domains such as Biochemistry, Genetics and Molecular Biology, Physics and Astronomy, Agricultural and Biological Sciences, Earth and Planetary Sciences, and Energy. These articles likely explored the applications of deep learning in specific contexts within these subject areas. Deep learning has found applications in bioinformatics, genomics, physics simulations, environmental monitoring, and energy optimization, among others.

Table 2. Subject areas of included papers.

Field	Number of Papers
Computer Science	14
Decision Sciences	6
Engineering	6
Medicine and Dentistry	6
Business, Management, and Accounting	5
Biochemistry, Genetics, and Molecular Biology	2
Physics and Astronomy	2
Agricultural and Biological Sciences	1
Earth and Planetary Sciences	1
Energy	1

4.2. Publishing Year

The included articles in the systematic review spanned a wide range of publishing years, reflecting the evolution and increasing interest in deep learning and neural networks for decision making (Figure 5). The distribution of articles across the years indicates the progression of research and the growing significance of this field. The earliest publication identified in the search was from 2017. The distribution of articles across the years in the review was as follows: 2017 (n = 1, 4%), 2018 (n = 3, 12%), 2019 (n = 5, 20%), 2020 (n = 3, 12%), 2021 (n = 5, 20%), and 2022 (n = 8, 32%). This distribution indicates a progressive growth of research in deep learning and neural networks for decision making over time. The higher number of articles in the later years, particularly in 2021 and 2022, suggests a surge in interest and research activity in this area.

The increasing trend in publications can be attributed to several factors. Firstly, advancements in computational power and the availability of large datasets have facilitated the application of deep learning and neural networks in decision-making tasks. Additionally, the rapid development of deep learning frameworks, tools, and algorithms has made it more accessible for researchers to explore and apply these techniques in their studies. Moreover, the practical success stories and promising results achieved through the application of deep learning in decision making have fueled further interest and research in this field.

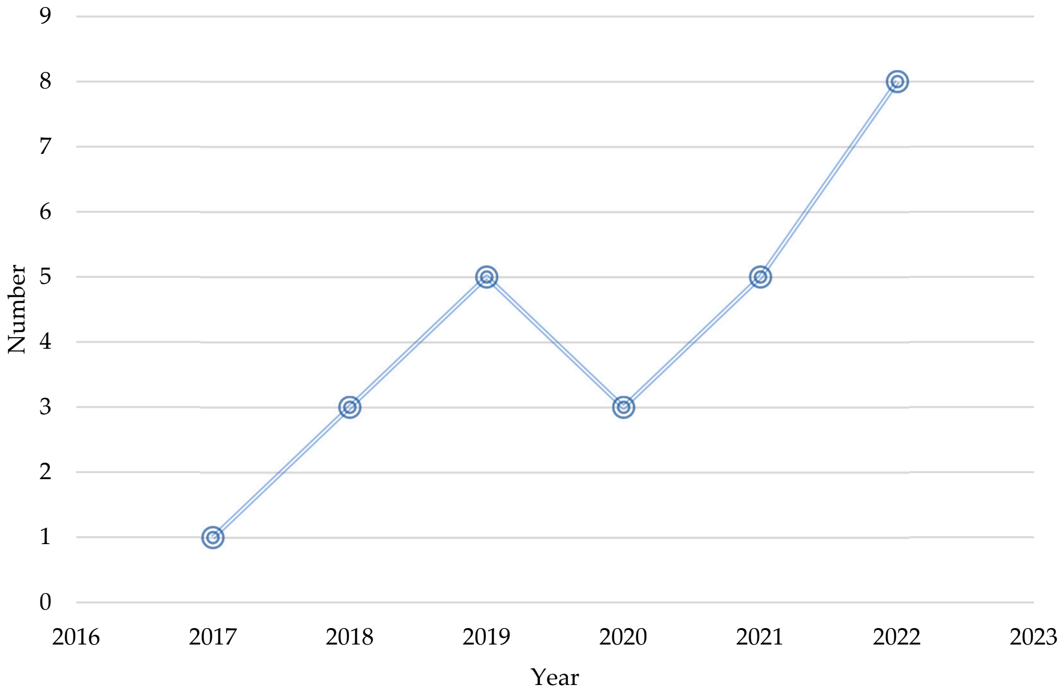

Figure 5. The number of included papers (2017–2022).

5. Decision-Making Models and Frameworks

Decision-making models and frameworks play a crucial role in various domains, including healthcare, transportation, energy, and more. In the healthcare domain, CNNs have been utilized by Liu et al. [84] for the assessment and diagnosis of pressure ulcers. These CNN-based systems provide valuable insights and support decision-making processes in medical diagnostics. Additionally, the integration of pattern recognition components, such as PANN, enhances the accuracy and efficiency of medical decision making [85].

The transportation domain has witnessed advancements in intelligent decision making for automated vehicles. CNNs have been leveraged by Cheng et al. [86] to make informed decisions, ensuring safe and efficient transportation. Moreover, deep learning techniques have been applied by Li et al. [87] to automate decision making in highway pavement preventive maintenance, contributing to improved infrastructure management. In the energy domain, intelligent energy-management systems for microgrids have been developed by El Bourakadi et al. [88] based on deep learning LSTM prediction models and fuzzy decision-making approaches. These models enable efficient energy allocation and optimize the performance of microgrids.

Across different domains, decision-making models have been extended to tackle general applications. For instance, the combination of deep learning, fuzzy logic, and multicriteria decision-making (MCDM) analysis has been employed by Costache et al. [89] to address flash-flood hazards. This approach, utilizing the H_2O R package, provides accurate predictions and assists decision-making processes in flood management. Furthermore, the utilization of deep learning techniques has been expanded by Vo et al. [90] into socially responsible investments and portfolio optimization. Deep learning models aid decision-makers in making informed investment choices while considering the social impact of their decisions.

In summary, decision-making models and frameworks have been applied to various domains, including healthcare, transportation, energy, and general applications. The integration of deep learning, CNNs, fuzzy logic, and MCDM analysis contributes to accurate and intelligent decision making, enhancing efficiency and effectiveness across different fields. Table 3 provides an overview of the decision-making frameworks mentioned in the titles and the corresponding domains.

Table 3. Decision-making frameworks and their associated domains.

Decision-Making Framework	Domain	Reference
CNN	Healthcare: Pressure ulcer assessment system	[84]
	Transportation: Intelligent decision making for automated vehicles	[86]
	General: Flash-flood hazard prediction	[89]
	General: Socially responsible investments and portfolio optimization	[90]
PANN	Healthcare: Pattern recognition in medical diagnostics decision making	[85]
Fuzzy Logic	General: Flash-flood hazard prediction	[89]
	General: Micro-grid energy management	[88]
	Opinion mining: Integration with CNN	[91]
MCDM Analysis	General: Flash-flood hazard prediction	[89]
H_2O R Package	General: Flash-flood hazard prediction	[89]
LSTM	Energy: Intelligent energy management for micro-grid	[88]
Dimension-Reduction Method	Healthcare: Medical decision making	[92]
Deep Learning	Healthcare: Deep neural networks for health decision making	[93]
	Transportation: Automated highway pavement maintenance	[87]
	General: Socially responsible investments and portfolio optimization	[90]

5.1. Improved Accuracy and Performance in Decision Making

Deep learning has emerged as a powerful tool, revolutionizing decision-making processes and enhancing accuracy and performance. CNNs have proven effective in diagnosing medical conditions, providing accurate assessments, and improving decision making regarding patient care [84]. The integration of CNNs and fuzzy logic allows for comprehensive and precise analysis, supporting informed choices in various decision-making scenarios [91]. Intelligent decision making for automated vehicles has significantly improved through the use of CNNs. These systems analyze data from sensors in real time, ensuring safety and efficiency in transportation [86]. In the energy sector, an intelligent energy management system utilizes deep learning LSTM prediction models and fuzzy decision making to optimize energy allocation, enhancing efficiency and enabling better decision making [88].

Deep learning techniques have also made significant contributions to flash-flood hazard assessment. By employing the H_2O R package and fuzzy-MCDM analysis, accurate predictions and risk assessments can be made [89]. Furthermore, deep learning supports decision making in socially responsible investments and portfolio optimization by analyzing vast amounts of data and aligning investment strategies with ethical practices [90]. Automated decision making based on deep learning has proven beneficial in highway pavement preventive maintenance. These systems accurately identify and prioritize maintenance tasks, optimizing decision-making processes and streamlining operations [87]. In conclusion, deep learning has brought about significant improvements in decision making. By leveraging techniques such as CNNs, fuzzy logic, and LSTM prediction models, decision-makers are empowered with comprehensive insights, enabling informed choices and driving positive outcomes.

5.2. Challenges and Limitations of Deep Learning and Neural Networks

The ability of deep learning and neural networks to analyze vast amounts of data, recognize patterns and make predictions has opened up new possibilities and enhanced decision making in numerous domains [93]. However, it is crucial to understand the challenges and implications associated with utilizing these technologies in decision-making contexts. One significant implication of deep learning in decision making is the reliance on data quality and quantity [84]. Deep learning models require large and diverse datasets to effectively train and generalize their learnings. The availability and accessibility of high-quality data play a crucial role in the success and accuracy of these models [90]. Obtaining labeled data can be time-consuming and expensive, particularly in specialized domains where domain expertise is required [85]. Furthermore, biases and limitations present in the training data can impact the decisions made by deep learning models, potentially leading to biased or suboptimal outcomes [91]. It is essential to ensure that the data used for training are representative, balanced, and free from biases to mitigate such risks.

Another implication of deep learning in decision making is the interpretability of the models. Neural networks are often referred to as "black boxes" due to their complex architectures and the difficulty in understanding the reasoning behind their decisions [87]. This lack of interpretability can be a significant concern, particularly in critical decision-making scenarios where transparency and accountability are paramount. Stakeholders and decision-makers may hesitate to fully trust the decisions made by deep learning models if they cannot explain how and why a particular decision was reached [86]. Developing techniques and approaches to enhance the interpretability and explainability of deep learning models is an ongoing research area that seeks to address this limitation.

The computational requirements of deep learning models also pose implications for decision-making processes. Training and running complex neural networks demand significant computational resources, including high-performance hardware and large-scale distributed computing systems [88]. The computational cost can limit the accessibility and scalability of deep learning solutions, particularly for individuals or organizations with limited resources [92]. Additionally, the time required for training deep learning models can be extensive, hindering real-time or time-sensitive decision-making applications. Balancing computational efficiency and accuracy is a crucial consideration in deploying deep learning models for decision-making purposes. Ethical considerations and concerns arise when employing deep learning in decision making. The responsibility lies not only in the design and development of the models but also in the ethical use and implications of the decisions made by these models [88]. Deep learning models can inadvertently reinforce biases present in the training data, leading to discriminatory or unfair outcomes [93]. For example, in decision making related to hiring processes or loan approvals, biased models can perpetuate existing inequalities. It is crucial to carefully monitor, evaluate, and address potential biases and ethical concerns throughout the development and deployment of deep learning models for decision making.

Another implication of deep learning in decision making is the need for human oversight and intervention [86]. While deep learning models can automate and augment decision-making processes, it is essential to have human experts involved to provide context, domain knowledge, and critical judgment [92]. Human intervention can help validate and interpret the decisions made by deep learning models, ensuring they align with ethical standards and desired outcomes [89]. The collaboration between humans and deep learning models can lead to more informed and robust decision making. Additionally, the integration of deep learning models into existing decision-making frameworks and systems poses challenges [87]. Incorporating these models requires careful consideration of compatibility, interoperability, and their potential impacts on existing processes. Decision makers need to evaluate the cost-effectiveness and feasibility of integrating deep learning models into their decision-making workflows, ensuring that the benefits outweigh the challenges and potential disruptions [90].

The rapid advancements in deep learning and neural networks also raise concerns about the potential displacement of human decision makers [88]. As these technologies continue to improve and demonstrate superior performance in certain decision-making tasks, there is a possibility that human decision makers may be replaced or marginalized. However, it is important to recognize that the strengths of human decision making, such as ethical reasoning, empathy, and contextual understanding, cannot be fully replicated by machines [86]. Instead, deep learning models should be seen as tools to augment and support human decision making rather than replace it entirely. In conclusion, deep learning and neural networks offer tremendous potential to enhance decision making processes across various domains [93]. However, their utilization also presents challenges and implications that need to be carefully addressed. Data quality, interpretability, computational requirements, ethical considerations, human oversight, integration, and the role of human decision makers are among the key factors that need to be considered [84]. By understanding and addressing these challenges, the power of deep learning can be harnessed to make more informed, ethical, and effective decisions in a wide range of applications [90].

6. Interdisciplinary Synergy in Deep Learning for Decision Making

This comparative analysis aims to evaluate and compare the performance of deep learning approaches in decision support systems across various domains. The study focuses on medical diagnosis, post-disaster decision making, financial analysis, affective computing, clinical decision support, and other related applications. By examining the strengths and limitations of different deep learning models within each category, this analysis provides insights into the effectiveness of these approaches. Furthermore, the importance of transparency, accountability, and explainability in AI-based decision support systems is emphasized. The findings of this study contribute to the understanding and advancement of deep learning techniques for decision-support purposes.

6.1. Medical Diagnosis

In the field of medical diagnosis, deep learning has proven to be highly effective. A deep learning-based decision support system developed by Taşkıran and Çunkaş [94] for diagnosing temporomandibular joint disorder showcased the potential of these models in enhancing diagnostic accuracy. Similarly, a clinical decision support system proposed by Salami et al. [95] utilizing deep learning techniques enabled accurate Alzheimer's diagnosis using the OASIS-3 dataset. These applications demonstrate the promising results of deep learning in medical decision support. A decision support system was created in a study by Arslan Tuncer et al. [96] to identify OSAS patients. Instead of using other parameters derived from polysomnographic data, such as those from the electrocardiogram, electroencephalogram, carbon dioxide measurements, and electromyography, the developed decision support system only used the Pulse Transition Time (PTT) parameter to classify patients and healthy individuals. The recommended approach used a deep learning approach to feature extract PTT signals. Two CNN models, AlexNet and VGG-16, were applied for feature extraction. The Support Vector Machine (SVM) and k-nearest neighbors (k-NN) algorithms were used to classify sick and healthy people using the features acquired. It was discovered that the study's performance was satisfactory when compared to other research in the published literature. Spänig et al. [97] created an AI that can interact with a patient (virtual doctor) using a speech recognition and speech synthesis system. This AI can interact with the patient autonomously, which is crucial for places like rural areas where access to primary medical care is severely constrained by low population densities. The system can predict type 2 diabetic mellitus (T2DM) using non-invasive sensors and deep neural networks as a proof of concept. Additionally, the approach offers a clear probability prediction for T2DM for a specific patient.

6.2. Post-Disaster Decision Making

Deep neural networks have emerged as valuable tools for post-disaster decision support [98]. By leveraging the power of deep learning, decision makers can make informed choices in response to disasters, minimizing risks and improving response strategies. Furthermore, Katzmann [99], in the study on explaining clinical decision support systems in medical imaging using cycle-consistent activation maximization, highlights the importance of interpretability in post-disaster decision-making processes.

6.3. Financial Analysis

Deep learning has shown great potential in financial analysis and decision support. Kraus and Feuerriegel [100], in the study on decision support from financial disclosures with deep neural networks and transfer learning, demonstrate the effectiveness of deep learning models in extracting valuable insights from financial data. However, challenges related to transparency and interpretability remain significant concerns.

6.4. Affective Computing

Text-based emotion recognition in decision support systems, developed by Kratzwald et al. [101], is a promising application of deep learning in affective computing. Kim et al. [102] suggested that the Explaining and Visualizing CNNs for Text Information (EVCT) framework improves the decision support system's accountability and transparency while maintaining its ability to model complicated text data. The EVCT framework offers a human-interpretable solution to the challenge of text classification while reducing information loss by implementing and improving cutting-edge techniques in NLP and image processing. By leveraging deep learning algorithms, decision support systems can consider emotional factors, improving the decision-making process. However, further research is needed to enhance the robustness of these models across different languages and cultural contexts.

6.5. Clinical Decision Support

Deep learning has significantly contributed to clinical decision support systems. Using a dataset of 5000 EHR records with information on patients suffering from numerous diseases, Khan and Shamsi [103] analyzed Health Quest, a deep learning-based model that uses EHR data to identify diseases in patients through unsupervised learning. This study may help to identify cases requiring continuous treatment for complicated illnesses and those requiring acute care in emergency rooms or other locations without appointments. Simeone et al. [104], in the study on Explaining and Visualizing CNNs for transparent AI decision support in medical imaging, emphasize the importance of interpretability and transparency in medical decision-making processes. Additionally, the development of a computer-assisted decision-support system for pulmonary cancer detection and stage classification on CT images by Masood et al. [105] highlights the potential of deep learning in automating clinical decision-support tasks. CT data were analyzed by Cha et al. with a cancer treatment response assessment (CDSS-T) that uses a combination of deep learning CNN and radiomic features to distinguish muscle-invasive bladder cancers that have fully responded to neoadjuvant treatment from those that have not. CDSS-T improved physician performance in identifying the complete response of muscle-invasive bladder cancer to neoadjuvant chemotherapy. To distinguish between muscle-invasive bladder cancers that have fully responded to neoadjuvant treatment and those that have not, Cha et al. [106] used deep learning CNNs and radiomic features to analyze CT data using the cancer treatment response assessment (CDSS-T). The CDSS-T helps doctors recognize a complete response to neoadjuvant treatment in muscle-invasive bladder cancer.

6.6. Other Applications

Deep learning has diverse applications beyond the aforementioned domains. van Dinter et al. [107], in their study on a deep learning-based decision support tool for solution recommendation in cloud manufacturing platforms, showcased the potential of deep learning in optimizing manufacturing processes. Furthermore, the development of a decision support system for automating document retrieval and citation screening by Niecikowski et al. [108] demonstrates the effectiveness of deep learning in streamlining information retrieval tasks.

The comparative analysis highlights the diverse applications of deep learning in decision support systems across medical diagnosis, post-disaster decision making, financial analysis, affective computing, clinical decision support, and other domains. While deep learning approaches have shown promise in improving decision-making accuracy, challenges related to interpretability, generalizability, and integration into existing workflows need to be addressed. Future research needs to focus on enhancing the transparency and explainability of deep learning models and validating their real-world performance to ensure reliable and effective decision support systems.

7. Future Directions and Research Opportunities

7.1. Emerging Trends and Technologies

Deep learning and neural networks are revolutionizing various fields with their advanced capabilities and decision-making implications. This section explores the emerging trends and technologies associated with deep learning and neural networks and delves into their implications for decision-making processes. Deep learning, a subset of machine learning, has gained significant traction in recent years. Its ability to automatically learn and extract intricate patterns from vast amounts of data has enabled breakthroughs in diverse domains such as image recognition, NLP, and recommendation systems [109]. As deep learning models become more complex and sophisticated, they offer unprecedented opportunities for decision making. Neural networks, inspired by the human brain's interconnected structure, form the backbone of deep learning algorithms. These networks consist of interconnected nodes, or "neurons," which process and transmit information. By leveraging this neural network architecture, deep learning algorithms can mimic human-like decision-making processes, leading to enhanced accuracy and efficiency in various applications [110].

One emerging trend in deep learning is the integration of generative models. These models, such as GANs and variational autoencoders (VAEs), can create new data samples that resemble the original training data. This capability has profound implications for decision making, as it enables the generation of synthetic data for training models in scenarios where acquiring real-world data is challenging or expensive. Another notable trend is the use of deep RL. By combining deep learning with RL, researchers have developed systems that can learn optimal decision-making strategies through trial and error. This approach has shown remarkable success in complex tasks, including game playing and robotics, where the agents learn to make decisions by interacting with their environments and receiving rewards or penalties based on their actions. Additionally, the emergence of explainable AI (XAI) techniques in deep learning has addressed the black-box nature of neural networks. XAI methods aim to provide insights into how deep learning models arrive at their decisions, increasing transparency and interpretability. This development is crucial for decision-making processes that require understanding and trust in the underlying mechanisms of AI systems [109].

Moreover, the application of deep learning and neural networks in decision support systems has gained momentum. These systems leverage the power of deep learning to analyze vast amounts of data, extract meaningful patterns, and provide decision-makers with valuable insights and recommendations. By integrating deep learning technologies into decision support systems, organizations can enhance their decision-making capabilities and gain a competitive edge in complex and data-driven environments [110]. The emerging trends and technologies in deep learning and neural networks have significant implications for decision making. With advancements in generative models, RL, ex XAI, and decision support systems, the power of deep learning can be harnessed to improve accuracy, efficiency, and transparency in decision-making processes across various domains [109].

Another recent development in deep learning is the construction of GPT, a large neural network that can generate natural language writings on a variety of topics and assignments. GPT, or Generative Pretrained Transformer, is based on the transformer architecture, which discovers the relationships between words and sentences through attention processes [111]. GPT can provide diverse and pertinent information and recommendations to decision-makers, which has a substantial impact on decision making. GPT, for example, can be used to create summaries of extensive papers or studies, allowing decision-makers to quickly grasp the key concepts and outcomes [112].

7.2. Interdisciplinary Collaboration and Integration

By bringing together experts from diverse domains, deep learning, and neural networks have benefited from a rich exchange of knowledge and perspectives. This collaborative approach has yielded several implications for decision-making processes. The integration of multiple disciplines, such as computer science, statistics, mathematics, and cognitive science, has led to the development of more robust and accurate deep-learning models. These models can effectively process and analyze complex data, enabling better decision making in various applications [109]. By combining expertise from different fields, researchers have been able to leverage insights from cognitive science to improve the interpretability and explainability of neural networks, making them more transparent and trustworthy for decision making [113].

Furthermore, interdisciplinary collaboration has played a vital role in addressing ethical concerns associated with deep learning and neural networks. By involving experts in fields like ethics, law, and social sciences, the potential biases and unfairness in decision-making algorithms can be identified and mitigated. This collaborative effort aims to ensure that these technologies are used responsibly and promote fairness and justice in decision-making processes [114]. Interdisciplinary collaboration has also facilitated the development of innovative applications of deep learning and neural networks in various domains. For example, the fusion of medical expertise and machine learning has enabled the creation of sophisticated diagnostic tools that can detect diseases with high accuracy [109]. Similarly, combining expertise from environmental science and data analysis has allowed researchers to develop models that can predict and mitigate the impact of natural disasters [110].

Moreover, interdisciplinary teams have been instrumental in translating research findings into practical solutions. By collaborating with industry professionals, policymakers, and end-users, researchers can effectively address real-world challenges and ensure the seamless integration of deep learning and neural networks into existing systems [114]. This collaborative approach promotes the adoption of these technologies in diverse sectors, leading to improved decision making and enhanced efficiency. The success of deep learning and neural networks in decision-making processes can be attributed to the emphasis on interdisciplinary collaboration and integration. By bringing together experts from various fields, these technologies have benefited from diverse perspectives, improved interpretability, addressed ethical concerns, fostered innovation, and facilitated practical implementation [110]. Moving forward, continued interdisciplinary collaboration will be crucial for unlocking the full potential of deep learning and neural networks in decision-making domains [114].

8. Conclusions

In most cases, a decision is made based on the output of the neural network's projected value for the relevant output factor or probability for various values of the relevant output factor. Decision making becomes more intelligent and precise thanks to deep learning technologies. There is greater time available for data analysis, processing, and application because manual data aggregation and document screening are less time-consuming tasks. The significance of the link between neural networks and decision making has been examined in this overview, along with the ways that deep learning techniques have enhanced decision making over the previous five years.

Decision-making models and frameworks have been used in a variety of fields, including healthcare, transportation, energy, and general applications, according to the 25 studies included in this study. Combining deep learning, CNNs, fuzzy logic, and MCDM can improve the efficacy and effectiveness of decision making across multiple industries. The comparative research illustrates the numerous uses of deep learning in decision support systems across various domains, including clinical decision support, post-disaster decision making, financial analysis, emotional computing, and medical diagnosis. Although deep learning techniques have shown promise in increasing the accuracy of decision making, issues with interpretability, generalizability, and integration into current processes still need to be resolved. To provide trustworthy and efficient decision support systems, future research needs to concentrate on boosting the transparency and explainability of deep learning models and validating their real-world performance.

Deep learning and neural network use also provide difficulties and ramifications that need to be properly considered. Among the important elements that need to be taken into account are data quality, interpretability, computational needs, ethical issues, human oversight, integration, and the role of human decision makers. The power of deep learning can be used to make better educated, moral, and efficient decisions in a variety of applications by comprehending and overcoming these obstacles. These technologies have benefited from multiple viewpoints, increased interpretability, addressed ethical concerns, stimulated creativity, and facilitated practical application by bringing together specialists from other sectors. The future of deep learning and neural networks in decision-making domains will depend heavily on continuing interdisciplinary collaboration. Future research could focus on enhancing the interpretability, generalizability, ethics, and validity of deep learning in decision making. Human-in-the-loop, combined AI techniques, and domain-specific applications need to be investigated further. Collaboration across disciplines will promote responsible AI adoption.

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Abbreviations

MCDM	Multi-Criteria Decision Making
AI	Artificial Intelligence
RL	Reinforcement Learning
FNN	Feedforward Neural Network
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
NLP	Natural Language Processing
LSTM	Long Short-Term Memory
GAN	Generative Adversarial Network
GRU	Gated Recurrent Unit
RBM	Restricted Boltzmann Machine
PTT	Pulse Transition Time
SVM	Support Vector Machine
k-NN	k-nearest Neighbors
T2DM	Type 2 Diabetic Mellitus
EVCT	Explaining and Visualizing CNNs for Text Information
CDSS-T	Cancer Treatment Response Assessment
VAE	Variational Autoencoder
XAI	Explainable AI

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