ASEAN Journal of Educational Research and Technology 4(1) (2025) 59-80

ASEAN Journal of Educational Research and Technology

Journal homepage: https://ejournal.bumipublikasinusantara.id/index.php/ajert

Evolution and Advancements from Neural Network to Deep Learning

H.M.M.N. Herath

University of Kelaniya, Srilanka

Correspondence: E-mail: malindah@kln.ac.lk

ABSTRACT

This systematic literature review explores the recent advancements, applications, and challenges in the field of deep learning. By analyzing a diverse array of primary studies, this review elucidates how deep learning technologies have evolved from simple neural network architectures to complex frameworks capable of transforming various scientific and industrial sectors. Key advancements discussed include significant theoretical developments aimed at enhancing model stability and predictability, the evolution of methodologies to ensure adversarial robustness, and the expansive application of deep learning across different domains such as facial recognition, autonomous navigation, and healthcare. The review also addresses critical challenges faced by the field, including the heavy reliance on large, annotated datasets, the substantial computational demands of advanced models, and the ethical concerns arising from the broader integration of these technologies. The findings suggest that future research should focus on developing more efficient unsupervised and semi-supervised learning techniques, enhancing computational algorithms, and fostering interdisciplinary collaborations to address ethical and practical challenges. This review highlights both the remarkable capabilities and the significant limitations of deep learning, providing insights into its future trajectory in the academic and practical realms.

ARTICLE INFO

Article History:
Submitted/Received 10 Nov 2024
First Revised 13 Dec 2024
Accepted 09 Feb 2025
First Available online 10 Feb 2025
Publication Date 01 Mar 2025

Keyword:
Computational demands,
Deep learning,
Evolution,
Neural network.

1. INTRODUCTION

Deep learning has emerged as a transformative force in artificial intelligence (AI), driving advancements across diverse fields such as computer vision, natural language processing, healthcare, and autonomous systems. At its core, deep learning relies on multi-layered neural networks to model complex patterns, enabling machines to perform tasks with unprecedented accuracy. Because of its ability to process vast amounts of data, deep learning has become an essential tool in modern AI applications (Aggarwal *et al*., 2022). However, as the field evolves, it faces key challenges, including computational demands, adversarial robustness, ethical concerns, and theoretical limitations (Javed *et al*., 2025).

One of the primary concerns in deep learning is its reliance on large, well-annotated datasets, which limits its accessibility in domains with scarce data, such as medical imaging and forensic analysis. Techniques such as data augmentation, transfer learning, and self-supervised learning have been developed to mitigate this limitation (Shujaat, 2025). Additionally, adversarial vulnerabilities remain a significant challenge, as deep learning models can be easily manipulated by carefully crafted perturbations, raising concerns about their security in critical applications (Jved *et al*., 2025). Research efforts have introduced adversarial training and defensive distillation techniques to improve the robustness of these models.

Theoretical advancements in deep learning have also gained traction, with researchers exploring the mathematical underpinnings of neural network optimization and training dynamics. The evolution of neural tangent kernels (NTK) and the integration of physics-informed AI provide deeper insights into model behavior, offering potential improvements in stability and interpretability (Di *et al*., 2023). Moreover, the development of neuroevolutionary strategies, such as Evolvable Neural Units (ENU), signifies a shift toward adaptive, self-learning AI models, further expanding deep learning's capabilities (Zhang & Mo, 2021).

Applications of deep learning continue to expand, influencing fields as diverse as facial recognition, autonomous navigation, and biomedical imaging. In facial recognition, deep learning models leverage convolutional neural networks (CNNs) and generative adversarial networks (GANs) to improve accuracy and reliability, but they also introduce privacy concerns and ethical considerations (Fuad *et al*., 2021). In autonomous navigation, reinforcement learning and deep Q-networks (DQNs) enable self-learning systems to optimize decision-making in dynamic environments, though explainable AI (XAI) remains crucial for ensuring transparency (Li *et al*., 2024).

The application of deep learning in medical imaging presents both opportunities and challenges. While AI-driven diagnostics enhance disease detection and patient care, the high-dimensional nature of medical data makes models prone to overfitting and requires extensive computational resources (Chen *et al*., 2022). Solutions such as hybrid learning models, federated learning, and multi-modal AI approaches aim to address these challenges, making deep learning more effective and adaptable in healthcare (Wang *et al*., 2022).

Furthermore, deep learning's role in criminal network analysis has gained prominence, offering insights into complex relational structures and behavioral predictions. Graph neural networks (GNNs) and attention-based models have demonstrated potential in detecting illicit activities and preventing cybercrime, but challenges related to data privacy and ethical AI deployment must be addressed (Ribeiro *et al*., 2023).

This study provides a comprehensive systematic literature review (SLR) to analyze recent advancements, key challenges, and future directions in deep learning. By investigating its

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

theoretical foundations, practical applications, and ongoing research efforts, this study aims to highlight the technological innovations and critical hurdles shaping the field. The novelty of this research lies in its holistic examination of deep learning across multiple domains, emphasizing the convergence of theoretical insights and real-world applications. The findings will contribute to the ongoing discourse on improving model efficiency, interpretability, and security, ultimately guiding the next generation of deep learning technologies.

To structure this analysis, the study addresses the following research questions: (i) How have recent advancements in neural networks contributed to the development of deep learning? (ii) What are the key differences between neural networks and deep learning, and how have they evolved over time? (iii) What are some of the current research areas and challenges in the field of deep learning, and how are they being addressed? These questions provide a foundation for exploring the evolution, impact, and future trajectory of deep learning, ensuring a focused and rigorous examination of its role in AI innovation.

2. METHODS

This study conducted a systematic literature review (SLR) to examine the advancement from neural networks to deep learning, following a structured methodology to ensure a comprehensive and methodical examination of existing research. The SLR approach is widely recognized as an effective method for reviewing literature within specialized fields (Kitchenham *et al*., 2009; Van Dinter *et al*., 2021; Pati & Lorusso, 2018). The systematic review process followed in this study is illustrated in **Figure 1**, which outlines the eight distinct phases of literature selection and analysis.

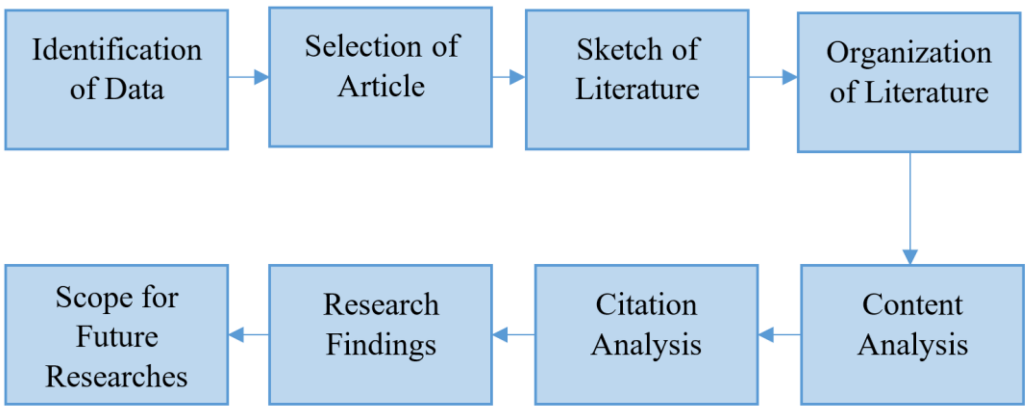

Figure 1. Systematic literature review (SLR) process for selecting research on the advancement from neural networks to deep learning.

To identify relevant studies, electronic database searches were performed using four widely recognized sources: Emerald Insight, IEEE, Google Scholar, and ResearchGate. The key search term "Advancement from Neural Networks to Deep Learning" was used across all databases. The inclusion criteria were limited to peer-reviewed journal articles published between 2018 and June 2023 to ensure a focus on recent developments in this field.

The sample selection followed a five-step filtering process:

(i) Initial Search – The first screening retrieved studies based on the key search term.
(ii) Period Filtering – Articles published before 2018 were excluded to maintain relevance to current advancements.
(iii) Field-Specific Search – Advanced search options were utilized to refine results based on subject relevance.

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

(iv) Abstract, Title, and Full-Text Screening – Articles were filtered based on whether the key term appeared in the abstract, title, or full text.

(v) Accessibility and Relevance Check – Only studies that were accessible to the researchers were considered. Articles that did not align with the research scope were excluded in this final step.

The filtering process resulted in a final selection of 32 peer-reviewed journal articles. **Table 1** provides a summary of the number of articles selected at each step from each database. The filtering process resulted in a final selection of 32 peer-reviewed journal articles. **Table 1** provides a summary of the number of articles selected at each step from each database.

To enhance the transparency and reliability of the systematic review, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) model was adopted. The PRISMA framework ensures a rigorous and methodical selection of studies, adhering to established best practices in systematic review and meta-analysis. **Figure 2** presents the PRISMA Flow Diagram, which visually maps out the selection and screening process, demonstrating the step-by-step approach taken to filter and refine relevant studies. This methodological roadmap ensures clarity, transparency, and reproducibility in the literature selection process.

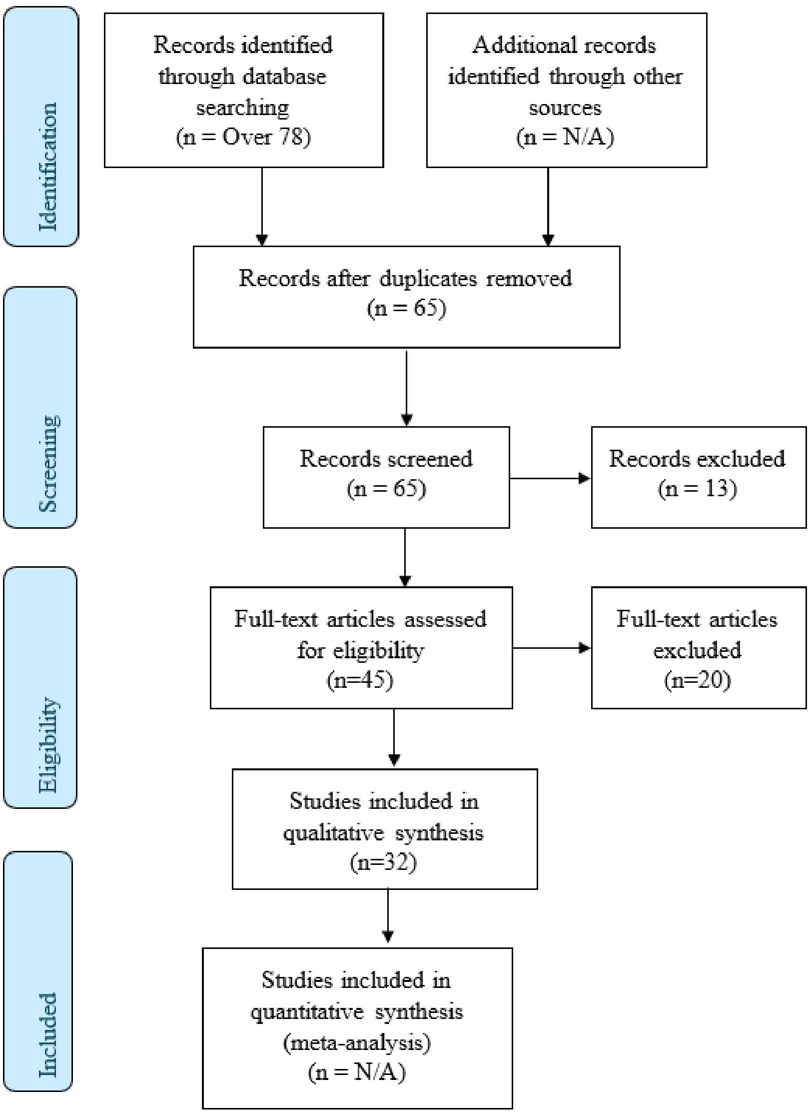

Figure 2. PRISMA flow diagram illustrating the selection and screening process for the systematic review.

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

Table 1. Sample selection process for systematic review.

Electronic Database	Number of articles				Final Sample
	Step 01 (Initial Search)	Step 02 (Filtered by Time Period)	Step 03 (Field-Specific Search)	Step 04 (Abstract & Full-Text Screening)	
Emerald Insight	12	8	5	3	3
IEEE	20	17	15	12	12
Google Scholar	25	22	13	10	10
Research Gate	21	18	12	9	9
Total	**78**	**65**	**45**	**32**	**32**

3. RESULTS AND DISCUSSION

3.1. Search Results

The search process, following the Systematic Literature Review (SLR) methodology and PRISMA framework, resulted in the selection of 32 peer-reviewed articles on advancements from neural networks to deep learning. The selected studies covered diverse topics, including deep learning architectures, theoretical advancements, adversarial robustness, and interdisciplinary applications. The structured methodology ensured a comprehensive representation of recent advancements because it filtered out irrelevant studies and focused only on high-quality, peer-reviewed research. The search and selection process are illustrated in **Figures 2** and **3**, while **Table 1** summarizes the final sample selection. **Figure 3** shows Systematic Literature Review (SLR) Process Flowchart. This diagram visually represents the step-by-step methodology followed in the systematic review, ensuring transparency, structure, and methodological rigor in the selection and analysis of literature.

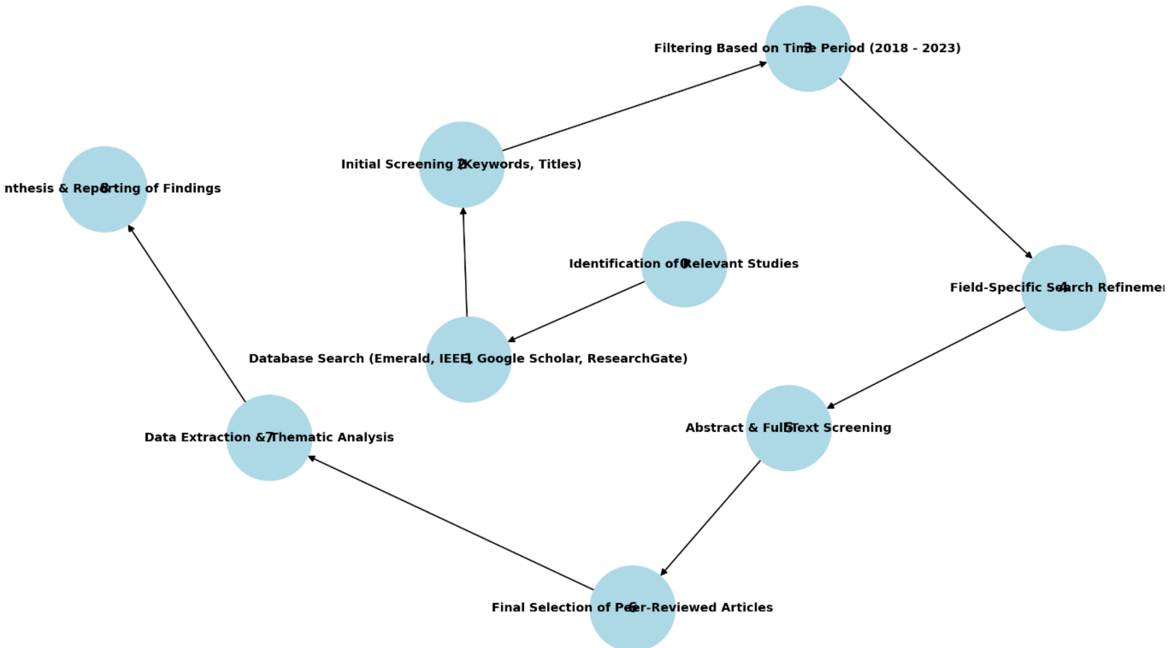

Figure 3. Systematic literature review (SLR) process flowchart.

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

3.2. RQ1: How have Recent Advancements in Neural Networks Contributed to the Development of Deep Learning?

Deep learning has significantly advanced multiple domains because of its ability to improve feature extraction, prediction accuracy, and computational efficiency. Research has demonstrated that deep learning has played a key role in face recognition, where architectures such as Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), and Generative Adversarial Networks (GANs) have enhanced detection and verification processes. However, challenges such as illumination, expression variations, and occlusions continue to limit model generalization. Some studies suggest that unsupervised learning techniques and 3D face recognition models could further improve robustness (Fuad *et al*., 2021).

Theoretical advancements have also been a focus in deep learning research, particularly in addressing the lack of theoretical depth. Recent studies have classified deep learning research into six key theoretical areas, including stochastic differential equations, geometric loss landscapes, and over-parameterization in neural networks. Establishing deep learning methods within solid mathematical frameworks has been emphasized as a way to enhance stability and predictability, reducing reliance on experimental results (Choundhary *et al*., 2022).

Several findings are concluded in the following:

(i) Adversarial Robustness and Security Concerns in Deep Learning. Security vulnerabilities in deep neural networks (DNNs) remain a critical concern because adversarial attacks can significantly impact model reliability. To address this issue, adversarial training has been proposed as a security-enhancing method, although it is computationally intensive. Research has categorized adversarial attacks and developed benchmark evaluation methods to assess model robustness. However, findings indicate that improving adversarial robustness may come at the cost of reduced accuracy on unaltered data, making security-performance trade-offs a key challenge in deep learning applications (Li *et al*., 2024).

(ii) Architectural Improvements and Application Areas. Advancements in CNN architectures have played a crucial role in improving image recognition, speech processing, and natural language processing (NLP). Loss functions, such as divergence and margin loss, have been identified as essential in optimizing training efficiency because they minimize discrepancies between predicted and actual outputs. CNNs have demonstrated strong performance in image segmentation, restoration, and feature extraction, making them widely applicable across various fields (Archana & Jeevaraj, 2024). Deep learning has also expanded into healthcare, NLP, and industrial systems, where its adaptability enables improvements in computational efficiency and predictive accuracy. Innovations such as privacy-enhanced federated learning, predictive maintenance, and electricity demand forecasting highlight the diverse capabilities of deep learning models in real-world applications (Martín & Camacho, 2022).

(iii) Deep Learning in Autonomous Systems and Network Analysis. The role of deep learning in autonomous navigation has gained significant attention because of its impact on mobile robotics, self-driving cars, unmanned aerial vehicles (UAVs), and space exploration. Researchers have explored methods for obstacle detection, scene perception, and path planning, emphasizing the need for real-time decision-making and high computational efficiency to handle dynamic environments (Aizat *et al*., 2023). Deep learning has also shown promise in the field of criminal network analysis, where graph convolutional networks have been used to analyze political corruption and financial crime

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

networks. Studies have demonstrated that GraphSAGE models outperform traditional machine learning techniques because they can efficiently process complex relational data, offering new opportunities for predictive crime analytics and law enforcement applications (Ribeiro *et al*., 2023).

(iv) Deep Learning in Criminal Network Analysis. Deep learning models have demonstrated an ability to predict missing links in criminal networks, classify relationships as criminal or non-criminal, and estimate future criminal behaviors, including recidivism. The ability of these models to generalize to unseen nodes enhances their applicability because criminal networks constantly evolve. This generalization is enabled by GraphSAGE, which does not rely on the entire graph structure, allowing scalability and efficiency in processing large datasets. As shown in **Figure 4**, deep learning techniques improve the recovery of missing partnerships in criminal networks by capturing hidden patterns that traditional criminology techniques fail to detect. Furthermore, these models effectively encode node and edge properties, making predictions in both classification and regression tasks more accurate. The capability to forecast the amount of money exchanged in criminal transactions, formation of new criminal partnerships, and likelihood of re-offending provides valuable tools for law enforcement agencies, surpassing the efficiency of conventional analytical methods (Ribeiro *et al*., 2023).

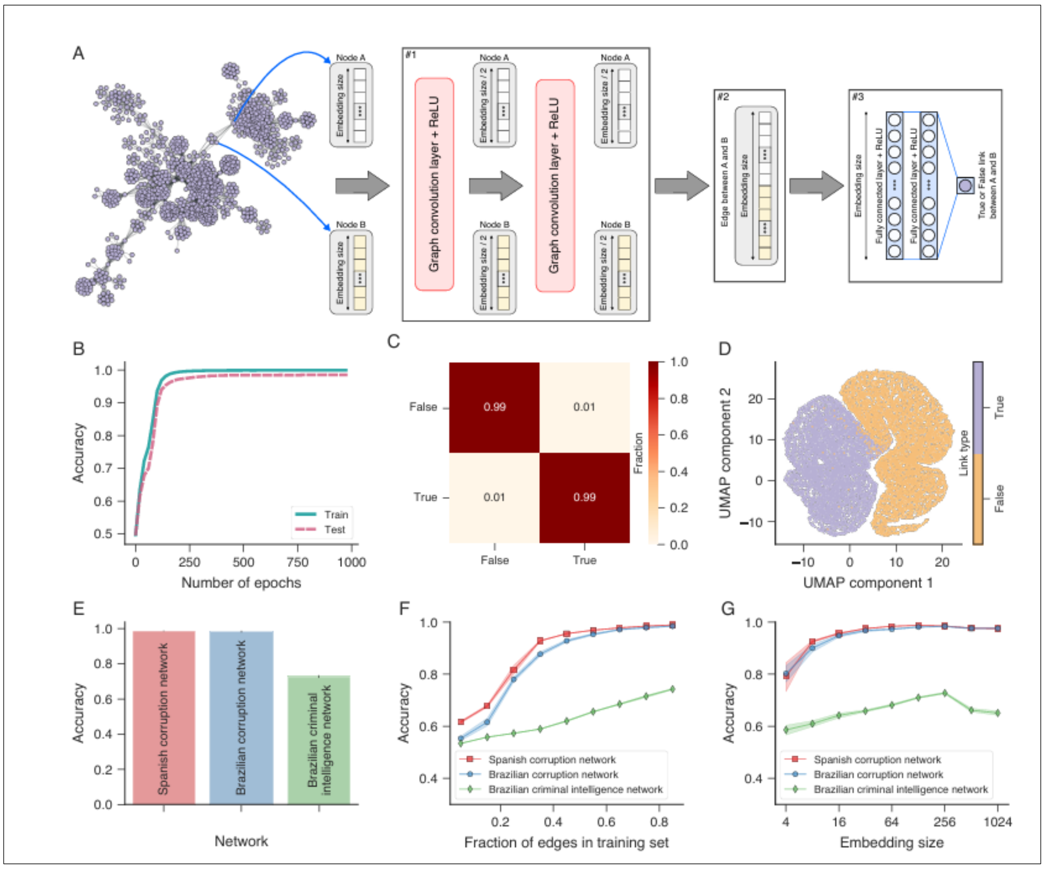

Figure 4. Recovering missing criminal partnerships with graph neural networks.

(v) Deep Learning in Structural Damage Identification. Deep learning has been integrated into civil engineering and structural damage detection, where supervised learning enables models to recognize structural flaws in buildings and infrastructure. Image recognition techniques allow unmanned aerial vehicles (UAVs) to autonomously inspect hazardous environments, reducing human risk exposure. These advancements enhance both accuracy and efficiency in assessing infrastructure conditions because deep learning models can process large-scale image datasets and detect subtle structural anomalies that traditional manual inspections might overlook (Pantoja *et al*., 2018).

(vi) Evolution and Expansion of Deep Learning Applications. Deep learning has undergone significant transformations, evolving from basic neural networks to models incorporating multiple hidden layers and nonlinear transformations. These advancements have expanded deep learning applications in image processing, natural language processing (NLP), and biometrics. The ability to integrate supervised and unsupervised learning techniques has improved prediction accuracy and processing speed because hybrid models leverage large datasets while minimizing computational overhead. Deep learning continues to advance medical diagnostics, security systems, and real-time decision-making technologies, solidifying its role in artificial intelligence applications (Najjar, 2023).

(vii) Deep Learning in Medical Image Processing. The application of deep learning in medical imaging has transformed traditional diagnostic processes. These models have been utilized for classification, segmentation, detection, and image registration, enabling faster and more precise disease detection. However, challenges persist because deep learning models require extensive, well-annotated datasets, which remain scarce in medical research. To address this limitation, unsupervised and semi-supervised learning techniques have been developed to extract meaningful patterns from unlabeled data, improving model training. As illustrated in **Figure 5**, models such as VoxelMorph have significantly enhanced image registration tasks, offering promising advancements in personalized healthcare (Chen *et al*., 2022).

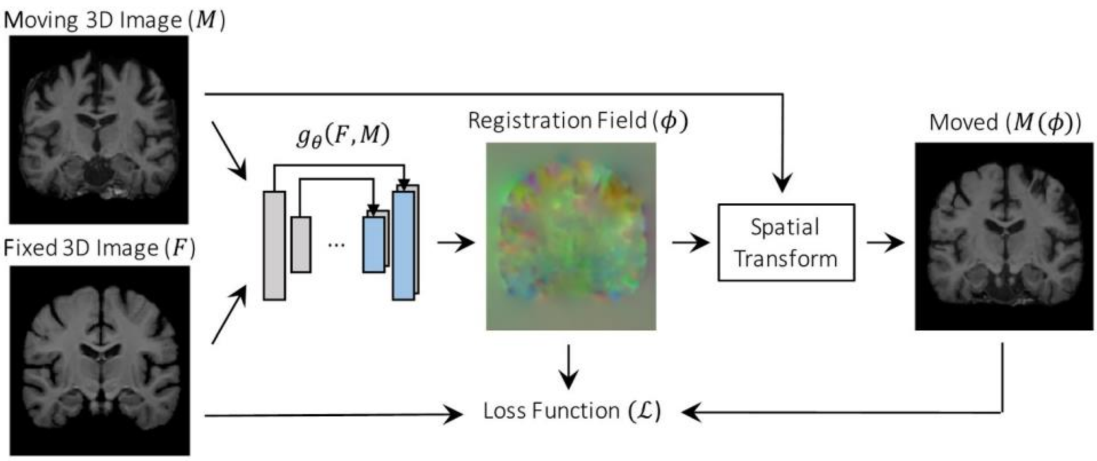

Figure 5. VoxelMorph for image registration in medical imaging.

(viii) Deep Learning in Protein Structure Prediction. The field of structural bioinformatics has seen a paradigm shift with the adoption of deep learning, particularly in protein structure prediction. Deep neural networks (DNNs) utilizing convolutional layers have significantly improved residue-residue contact prediction in proteins. These models outperform traditional prediction techniques because they capture hierarchical data representations, which are crucial for understanding complex protein interactions. The success of DNNs in Critical Assessment of Protein Structure Prediction (CASP) competitions has demonstrated their effectiveness, with notable improvements in accuracy across successive CASP rounds. Despite their progress, current DNN-based approaches still face limitations because of overfitting to training data, restricting their predictive power on

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

unseen sequences. Future research must focus on enhancing model generalizability to expand deep learning applications beyond protein structure prediction into fields such as protein design and drug discovery (Kandathil *et al*., 2019).

The reviewed literature underscores the rapid evolution of deep learning architectures, theoretical foundations, and application areas. While CNNs, GANs, and DBNs have significantly improved feature extraction and learning accuracy, challenges such as adversarial robustness, computational efficiency, and data privacy remain crucial. Findings suggest that deep learning models need continuous adaptation because technological advancements introduce both new opportunities and security risks.

The reviewed literature highlights the transformational impact of deep learning across multiple disciplines, including law enforcement, engineering, medicine, and bioinformatics. While advancements in criminal network analysis, medical imaging, and structural diagnostics showcase deep learning's practical benefits, several challenges remain. Data scarcity, computational costs, and adversarial robustness pose significant obstacles because deep learning models require extensive training and optimization.

Deep learning is expected to continue shaping diverse fields, including healthcare, autonomous navigation, cybersecurity, and criminal analytics. Future research should focus on developing lightweight, explainable deep learning models because real-time decision-making and ethical AI concerns are becoming increasingly important. The integration of unsupervised learning, federated learning, and quantum computing may provide breakthroughs, making deep learning systems more scalable, interpretable, and secure.

Deep learning will continue to evolve as researchers explore hybrid learning models, unsupervised techniques, and federated learning to overcome current limitations. The findings indicate that future developments in deep learning will focus on improving model interpretability, security, and efficiency, making artificial intelligence more accessible and adaptable across industries

3.3. RQ2: What are the Key Differences between Neural Networks and Deep Learning, and How have They Evolved Over Time?

Neural networks serve as the foundational building blocks of deep learning because they provide the computational framework for multi-layered models capable of performing classification, prediction, and generative tasks. Over time, the complexity of these networks has increased significantly, incorporating architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The evolution of deep learning has been driven by automated methods, such as CoDeepNEAT, which optimize network architectures through evolutionary algorithms. These automated approaches have achieved performance comparable to human-designed models in domains like object recognition and language processing, demonstrating the efficiency of automated deep learning design (Manakitsa *et al*., 2017).

The CoDeepNEAT framework, as depicted in **Figure 6**, extends traditional neuroevolution techniques by optimizing not just the weights but also the topologies and hyperparameters of deep neural networks. The framework assembles networks through coevolutionary processes, combining modules and blueprints to form deep, structured architectures commonly seen in high-performing DNNs. By applying this approach to CIFAR-10 image classification and real-world image captioning, studies have shown that automatically generated DNN architectures can match or even surpass human-crafted networks, significantly reducing manual design efforts (Manakitsa *et al*., 2024).

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

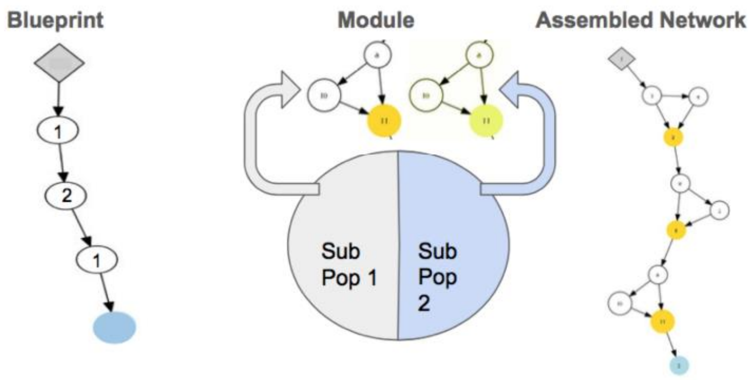

Figure 6. Visualization of how CoDeepNEAT assembles networks for fitness evaluation.

Several aspects are in the following:

(i) Historical Progression of Deep Learning Architectures. The transformation of deep learning models can be traced back to early neural network theories, progressing through key technological milestones such as the perceptron, backpropagation techniques, and deep belief networks. These advancements have played a crucial role in enhancing model accuracy, training stability, and computational efficiency. CNNs, RNNs, and other deep architectures have enabled deep learning models to outperform traditional neural networks in applications such as image recognition and natural language processing. The historical perspective on neural networks provides insights into how incremental improvements in training techniques, computational power, and algorithmic efficiency have shaped modern deep learning (Alom *et al*., 2019).

(ii) Training Dynamics and Theoretical Insights into Neural Networks. Research into neural network training dynamics has provided a deeper understanding of how deep neural networks transition from chaotic learning behaviors to stable performance optimization. Early training phases exhibit behavior similar to Neural Tangent Kernels (NTK), where deep networks behave as linearized models with gradual weight updates. However, as training progresses, these dynamics shift into nonlinear behavior, allowing DNNs to learn complex functions beyond what traditional linear models can capture. These insights have enhanced the predictability and interpretability of deep learning models because they provide a theoretical foundation for understanding how deep networks generalize data (Fort *et al*., 2020). The conceptual overview of deep learning phenomenology, illustrated in **Figure 7**, showcases the evolution of learning dynamics across different neural architectures, emphasizing the nonlinearity of deep learning optimization. Understanding these intricate learning behaviors is crucial for developing more robust and stable deep learning architectures (Fort *et al*., 2020).

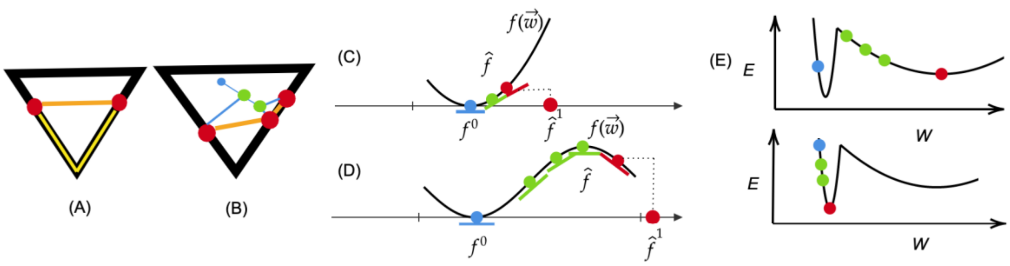

Figure 7. Conceptual overview of diverse deep learning phenomenology.

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

(iii) Comparison of Standard Deep Learning Training and NTK Models. The study contrasts the training behaviors of standard deep learning models with those predicted by Neural Tangent Kernel (NTK) models because deep neural networks (DNNs) exhibit highly nonlinear training dynamics that deviate significantly from their initialization points. While NTK-based models assume a linear expansion of weights, deep learning models undergo a rapid, chaotic evolution in the initial training phase. This phase is crucial because it dictates the trajectory of the model's convergence towards lower-loss basins in the parameter space, ultimately influencing both performance and stability. The findings suggest that deep learning models explore more complex function regions than NTK counterparts because they dynamically adjust internal feature representations through iterative training. The early instability observed in training highlights the importance of adaptive learning schedules and robust optimization techniques in modern deep learning architectures. This nuanced understanding challenges conventional views, emphasizing that both linear and nonlinear training dynamics must be considered to fully grasp how deep learning models evolve over time (Ching *et al*., 2018).

(iv) Biologically Inspired Neural Networks and Evolvable Neural Units (ENU). A novel biologically inspired model, termed the Evolvable Neural Unit (ENU), integrates neuroscience, machine learning, and evolutionary algorithms to mimic the behavior of biological neurons and synapses. Unlike traditional deep learning models, ENUs allow individual neurons and synapses to evolve, leading to emergent learning rules such as spike-timing-dependent plasticity. This adaptability enables agent-based learning, where networks develop their own learning mechanisms rather than relying on explicitly programmed rules. As depicted in **Figure 8**, the ENU framework introduces a new paradigm for artificial intelligence, allowing neural networks to evolve in a manner that resembles biological intelligence. By leveraging evolutionary strategies, these networks effectively discover spiking dynamics and reinforcement learning mechanisms, making them suitable for complex decision-making tasks. The study demonstrates the potential for evolved networks to autonomously navigate environments like a T-maze, suggesting a shift toward dynamic, self-adapting AI systems (Dasgupta *et al*., 2013).

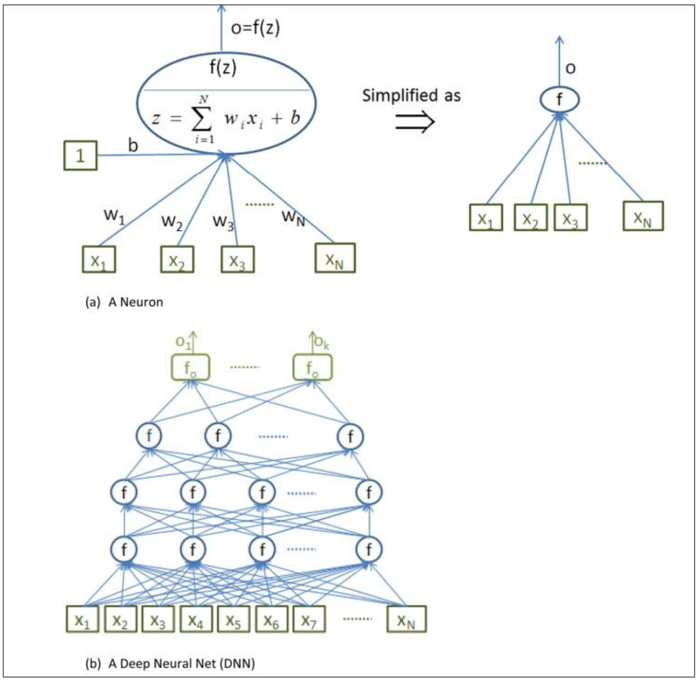

Figure 8. Architecture of deep neural networks.

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

(v) Training Dynamics and Evolution of Deep Learning Architectures. Deep learning models have undergone significant evolution because of the need to process increasingly large datasets and extract complex hierarchical features. Unlike early shallow neural networks, which consisted of a few layers and required manual feature extraction, modern DNNs utilize deep architectures like CNNs and RNNs that automatically learn representations from data. This transition was driven by advances in hardware, optimization techniques, and training methodologies, allowing deep networks to outperform traditional approaches in fields such as computer vision, natural language processing, and medical diagnostics. The role of NTK in training analysis further underscores how deep learning models move away from simple linear approximations towards highly dynamic, non-linear transformations, which are essential for achieving superior predictive capabilities (Lee, 2023).

(vi) Deep Learning in Pharmaceutical Applications (QSAR Models). Deep learning models have also redefined Quantitative Structure-Activity Relationship (QSAR) modeling in the pharmaceutical industry because they overcome the limitations of traditional neural networks. Early QSAR models in the 1990s suffered from overfitting, slow convergence, and inefficiencies in processing large datasets, leading to their replacement by support vector machines (SVMs) and random forests (RFs) in the early 2000s. However, with the resurgence of deep learning, modern QSAR models leverage deep neural networks (DNNs) to process vast chemical datasets and identify hidden patterns in molecular structures. The transition from shallow networks to DNN-based QSAR models has improved drug discovery efforts because deep learning networks can learn complex molecular representations without requiring hand-engineered features. This shift underscores the increasing reliance on automated feature learning and scalable architectures in pharmaceutical applications, demonstrating the broader impact of deep learning advancements in diverse scientific domains (Rane *et al*., 2024).

(viii) Neural Tangent Kernel (NTK) and Evolution of Deep Learning Architectures. The study explores the evolution of deep learning architectures through the concept of Neural Tangent Kernel (NTK) because NTK provides a theoretical framework for understanding how modern deep networks refine their internal structures over time. Traditional neural networks relied on fewer layers with simpler connections, limiting their ability to capture hierarchical patterns in data. In contrast, deep learning employs multiple nonlinear layers, enabling the hierarchical extraction of increasingly abstract features, making tasks such as image and speech recognition more effective. Over time, the expansion of computational resources and deeper theoretical insights facilitated the transition from shallow models to highly optimized architectures that balance efficiency and accuracy. This shift underscores how deep learning frameworks maintain static architectures yet refine internal parameters to optimize performance, a fundamental distinction from earlier, dynamically altering models (Latendresse *et al*., 2024).

(ix) From Early Artificial Neural Networks (ANNs) to Deep Neural Networks (DNNs). The historical progression from Artificial Neural Networks (ANNs) to DNNs has been shaped by the need for improved feature learning and scalability because early models such as the perceptron, developed in the 1950s, struggled with complex pattern recognition due to shallow architectures and limited computational power. These early networks suffered from challenges like the curse of dimensionality, making them ineffective for handling large-scale datasets. With the advent of deep learning, these limitations were addressed through multi-layered architectures, backpropagation, and scalable optimization techniques. Unlike simple ANNs, DNNs now effectively leverage large

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

datasets to learn hierarchical representations, excelling in tasks such as image classification, speech processing, and natural language understanding. The evolution of learning algorithms from Hebbian learning to backpropagation played a crucial role in this transformation, enabling deep networks to train efficiently and generalize better to unseen data (Wang *et al*., 2022).

(x) The Expansion of Deep Learning into Large-Scale AI Applications. Deep learning has significantly expanded into large-scale artificial intelligence applications because its multi-layered networks allow machines to extract meaningful features from complex, high-dimensional datasets autonomously. Unlike traditional shallow networks, which required manual feature extraction, modern deep learning systems can automatically learn representations from raw data, making them ideal for computer vision, speech recognition, and autonomous systems. As computational power has increased and algorithms have improved, deep learning has shifted from manually programmed models to self-learning architectures capable of understanding nuanced data patterns with minimal supervision. This shift has enabled more efficient handling of large-scale data, driving advancements in fields such as biomedical imaging, cybersecurity, and real-time decision-making systems. The integration of deep learning into these domains illustrates its ability to generalize across tasks, a defining characteristic that sets it apart from traditional neural networks (Mishra & Gupta, 2016).

(xi) Deep Learning in Computer Vision and Pattern Recognition. The study examines how deep learning has redefined computer vision and pattern recognition tasks because its ability to learn hierarchical feature representations has improved object recognition, scene understanding, and anomaly detection. Unlike early neural networks, which struggled with variations in scale, orientation, and noise, modern deep learning models employ advanced architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to efficiently process spatial and temporal data. As depicted in **Figure 9**, deep learning architectures can differentiate between objects in complex environments more accurately than traditional methods because they learn multi-level representations, reducing dependence on handcrafted features. This capability has led to breakthroughs in facial recognition, medical imaging, and autonomous navigation, where precise classification and detection are critical (Wang *et al*., 2022).

Figure 9. Two objects that can be recognized differently by deep learning architecture.

(xii) Deep Learning Innovations and Transition from Traditional Neural Networks. Deep learning has driven significant innovations across multiple domains because it outperforms traditional machine learning in adaptability and efficiency. Unlike earlier models that relied on manually designed feature extraction, deep learning employs

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

automated feature learning, enabling systems to adapt dynamically to complex environments. This shift has been pivotal in developing intelligent applications that require continuous learning, such as autonomous navigation, medical diagnostics, and financial forecasting (Mishra & Gupta, 2016).

(xiii) Mathematical Foundations of Deep Learning and Non-Linear Transformations. The transition from traditional neural networks to modern deep learning systems has been fundamentally driven by mathematical advancements in non-linear transformations because earlier models, which were predominantly linear, struggled with complex pattern recognition tasks. Traditional neural networks were inspired by biological neuron models, designed for rapid information processing but limited in their ability to capture intricate relationships within data. Early networks were constrained to basic classification and regression tasks because they lacked the ability to generalize beyond linear boundaries. The incorporation of activation functions such as ReLU and Sigmoid allowed for deeper architectures that could extract hierarchical representations from data, leading to vast improvements in predictive accuracy (Rane *et al*., 2024).

(xiv) Evolution from Shallow to Deep Learning Architectures. The evolution of deep learning has been characterized by the transition from shallow neural networks to deep architectures, because deeper models build increasingly abstract representations at each layer. Unlike traditional neural networks, which relied on a few layers for direct feature mapping, deep learning employs multiple hidden layers to progressively refine the data representation, allowing for higher accuracy in complex pattern recognition tasks. Modern deep networks have revolutionized fields such as image recognition, speech processing, and autonomous systems because they leverage multi-layered architectures that enhance hierarchical learning. Unlike conventional neural networks, which required extensive manual tuning, deep learning systems automatically learn and optimize hierarchical features, reducing human intervention in model design and improving generalization across diverse datasets (Rane *et al*., 2024).

(xv) Optimization and Function Approximation in Deep Learning. The ability of deep learning models to approximate complex functions is a key factor in their success because deep architectures optimize multi-dimensional representations more effectively than shallow networks. This mathematical insight explains why deep networks outperform traditional models, as they capture non-linear dependencies that shallow models fail to represent accurately. Deep learning enhances model performance because it optimizes weights across multiple layers, improving the network's ability to extract essential patterns from data. Unlike shallow networks, which often get stuck in local minima, deep learning models use advanced optimization techniques like stochastic gradient descent and backpropagation to reach more optimal solutions, reducing errors and improving accuracy (Rane *et al*., 2024).

The review confirms that deep learning has evolved through both architectural advancements and theoretical refinements, leading to more scalable, interpretable, and high-performing models. While automated design techniques like CoDeepNEAT have reduced human effort in optimizing neural network architectures, research into training dynamics and loss landscapes has provided a stronger mathematical foundation for deep learning.

Despite these advancements, challenges remain because deep learning models require large computational resources and are prone to adversarial vulnerabilities. Future research should focus on enhancing model efficiency, improving interpretability, and incorporating hybrid learning approaches that blend supervised, unsupervised, and reinforcement learning. As deep learning continues to evolve, the integration of neuroevolutionary techniques,

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

physics-informed AI, and federated learning is expected to further refine model design and application across various industries.

The evolution of deep learning has been marked by advancements in network architectures, biologically inspired learning, and domain-specific optimizations. The key takeaways from this analysis include:

(i) The divergence between standard deep learning and NTK-based models, emphasizing the role of nonlinear training dynamics in DNN optimization.
(ii) The introduction of Evolvable Neural Units (ENU), which shift AI development toward adaptive, self-learning models.
(iii) The historical transformation of QSAR modeling, demonstrating how deep learning has redefined drug discovery and pharmaceutical research.

The evolution of deep learning from simple neural networks to complex, multi-layered architectures has transformed artificial intelligence and machine learning because of advances in:

(i) Neural network depth and feature learning, enabling superior pattern recognition and decision-making.
(ii) Optimization techniques, such as backpropagation and dropout, which enhance training efficiency and generalization.
(iii) Hardware advancements, facilitating the scalability of deep learning models for industrial applications.

The mathematical underpinnings of deep learning provide a foundation for future advancements because understanding non-linearity, optimization, and hierarchical learning will drive the next generation of AI systems. Future research should explore hybrid models that integrate deep learning with evolutionary algorithms, improving adaptability and efficiency in real-world applications. This evolution underscores the transformative role of deep learning, setting the stage for more intelligent and autonomous AI systems capable of solving complex, real-world challenges.

Future research should focus on improving interpretability, efficiency, and adaptability in deep learning, particularly by integrating hybrid learning models, evolutionary AI techniques, and biologically inspired architectures to enhance model generalization and scalability. Also, future research should explore hybrid AI models that combine deep learning, evolutionary strategies, and biologically inspired networks, creating more adaptive and efficient AI systems capable of self-learning and optimization.

3.4. RQ3: What are Some of the Current Research Areas and Challenges in the Field of Deep Learning, and How are They being Addressed?

Deep learning research continues to evolve, addressing key challenges and expanding its applications across various domains. One of the primary concerns in this field is data scarcity, which significantly impacts model training because deep learning models require extensive datasets for robust performance. To mitigate this, researchers are employing techniques such as transfer learning, synthetic data generation, and semi-supervised learning. These methods enable models to generalize better even when data availability is limited.

Another crucial research area focuses on optimizing deep learning models for energy-efficient computing because traditional deep networks require substantial computational power. Researchers are exploring techniques like split computing and early exiting strategies to reduce the computational burden on mobile devices while maintaining high accuracy. These approaches improve the trade-off between inference speed and energy consumption, making deep learning more viable for real-time applications (Cheng *et al*., 2024).

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

In neuroimaging, deep learning has shown potential in enhancing outcome prediction, data interpretation, and segmentation. However, challenges such as multidimensionality, overfitting, and high computational costs persist because neuroimaging data is often complex and requires extensive preprocessing. Solutions include adopting multimodal learning strategies and implementing advanced visualization techniques to improve model interpretability (Xu *et al*., 2023).

Deep learning is also transforming evidence-based decision-making across various sectors because of its ability to extract complex patterns from large datasets. However, ensuring model transparency and reliability remains a challenge, as deep networks are often considered "black boxes." Researchers are developing interpretable deep learning models, incorporating attention mechanisms and self-explainable architectures to enhance trust in decision-making systems.

Biomedical imaging is another field where deep learning plays a crucial role because of its ability to enhance disease diagnosis and health profiling using large-scale imaging data. However, data imbalance and model generalization issues pose challenges because medical datasets often lack diverse representations. Researchers are addressing these issues by employing data augmentation techniques, ensemble learning, and domain adaptation (Wang *et al*., 2022).

Hybrid deep learning models are emerging as a solution to many existing limitations because they combine conventional architectures with novel approaches such as capsule networks, which improve spatial hierarchy representation. Future research is expected to focus on refining lightweight, efficient models that integrate seamlessly with real-world applications while maintaining high accuracy and adaptability (Wang *et al*., 2022).

Deep learning continues to expand across multiple disciplines, addressing key challenges while unlocking new opportunities. One of the prominent areas of development is biomedical imaging because deep learning models have shown remarkable improvements in segmentation accuracy, classification performance, and feature extraction. A multi-modal brain tumor segmentation framework using a hybrid attentional fusion scheme enhances segmentation results by effectively handling diverse input modalities. Similarly, a three-dimensional convolution attention neural network (3DCANN) for EEG emotion recognition improves classification accuracy because of its ability to extract both spatial and temporal features (Chen *et al*., 2022).

The field of artificial intelligence and machine learning has also seen advancements through Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Natural Language Processing (NLP), and Reinforcement Learning (RL). These techniques contribute to solving complex real-world problems because they facilitate enhanced feature extraction, data generation, and autonomous decision-making. However, scalability remains a challenge because handling large datasets with high dimensionality requires optimized network architectures, efficient memory storage, and computational trade-offs (Yang, 2023). Innovations such as improving GAN output diversity, refining NLP-based contextual understanding, and optimizing RL strategies for real-time applications further push the capabilities of deep learning.

Deep learning has made significant strides in biosciences, particularly in protein structure prediction, genome engineering, and systems biology, because of its ability to model intricate biological interactions. Despite this progress, challenges persist due to the requirement of extensive training data and computational resources. The adaptation of deep learning models to specific biological contexts remains a bottleneck because different biological systems present unique constraints in terms of data availability and generalization. Developing

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

efficient computational methods and improving multimodal data integration are essential steps toward enhancing the effectiveness of deep learning in biosciences (Sapoval *et al*., 2022).

In multiagent reinforcement learning (DMARL), deep learning facilitates more dynamic and adaptive AI systems because it enables agents to learn from interactions within multiagent environments. However, nonstationarity and increased computational complexity pose significant challenges because the strategies of individual agents evolve in real-time. Approaches such as centralized training with decentralized execution, opponent modeling, and enhanced coordination mechanisms have been explored to optimize agent behaviors. Additionally, incorporating insights from psychology and sociology into agent interactions enhances cooperative decision-making, making DMARL systems more robust and efficient (Wong *et al*., 2023).

Blockchain technology has been integrated with deep learning to enhance security, data integrity, and model transparency because deep learning models are often vulnerable to adversarial attacks and data manipulation. Blockchain provides decentralized storage and immutable records, ensuring reliability in sectors such as healthcare, industrial automation, and cybersecurity. However, computational efficiency, data privacy, and network scalability remain key challenges because blockchain networks introduce additional overhead. Optimizing blockchain architectures to handle deep learning model requirements is an ongoing research focus, ensuring that the synergy between these two technologies can be fully leveraged for secure AI applications.

Deep learning has demonstrated significant potential in various domains, including medical imaging, agriculture, and general artificial intelligence applications. In oncology, deep learning models have improved diagnostic accuracy, classification, and segmentation in bone tumor detection because they can analyze large and complex datasets with high precision. However, challenges such as data scarcity and computational intensity hinder widespread adoption. The integration of deep learning with emerging technologies can enhance model generalization, making it applicable across different clinical settings. This improvement could lead to more personalized treatment plans, enabling better patient outcomes because of deep learning's predictive capabilities in informing clinical decision-making (Zhou *et al*., 2022).

In broader artificial intelligence research, efforts are being made to address fundamental deep learning challenges, such as adversarial vulnerability, model interpretability, and environmental concerns associated with training large-scale models. Optimization techniques, including transfer learning and architectural enhancements, are being explored because they reduce reliance on extensive labeled datasets while maintaining performance. The development of more efficient network architectures and computational frameworks is essential to making deep learning more robust and scalable for diverse applications. Additionally, deep learning is being integrated with other artificial intelligence approaches to enhance interpretability and decision-making capabilities (Albahar, 2023).

The application of deep learning in agriculture has also gained momentum because of its ability to improve efficiency in fruit counting, soil management, weed detection, and yield prediction. However, the deployment of deep learning in this sector faces challenges, including limited labeled datasets, high computational costs, and the scarcity of deep learning expertise. Research suggests that cost-effective techniques and the integration of deep learning with IoT and robotic systems can improve the accessibility of artificial intelligence in agricultural settings. These advancements are crucial because they will enable automated and intelligent farming solutions, reducing reliance on traditional labor-intensive practices (Albahar, 2023).

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

General deep learning research continues to tackle the issue of model compositionality, particularly in handling long-tailed distributions and hierarchical data structures. Current models struggle with generalization beyond training data, making them vulnerable to adversarial attacks. Addressing this challenge requires novel architectures that incorporate domain knowledge and cognitive processing techniques. Deep learning models that integrate structured reasoning can improve robustness and interpretability because they allow models to constrain their learning process more effectively. By incorporating domain-specific rules, deep learning frameworks can achieve greater reliability in real-world applications (Wang *et al*., 2022).

3.5. Discussion

The systematic literature review highlights significant advancements in deep learning, while also identifying persistent challenges across various applications. The evolution of theoretical frameworks has aimed to enhance model predictability and stability because deep learning has been criticized for its heavy reliance on empirical evidence. Recent efforts focus on addressing these concerns by incorporating more robust theoretical foundations into model design, ensuring more reliable and interpretable outcomes (Aggarwal *et al*., 2022).

A critical challenge in deep learning is adversarial robustness, as models are susceptible to adversarial attacks that can compromise their reliability. To mitigate this, adversarial training methods have been developed, improving model resilience by enhancing their ability to distinguish between genuine and manipulated data. However, these methods require extensive computational resources, which limits their feasibility in resource-constrained environments. Additionally, as deep learning applications expand into security-sensitive domains such as facial recognition and autonomous navigation, ensuring robustness against adversarial interference remains a priority (Javeed *et al*., 2025).

Deep learning's applications extend to healthcare, autonomous navigation, and biometric recognition, each requiring domain-specific adaptations. In healthcare, deep learning is used for medical imaging analysis and disease diagnosis, but progress is hindered because of data dependency and scarcity. The lack of large, well-annotated datasets affects model generalization, particularly in specialized medical fields where data collection is expensive and time-consuming. To address this, researchers are exploring data augmentation techniques, federated learning, and synthetic data generation to reduce reliance on manually labeled datasets (Shujaat *et al*., 2025).

The computational demands of deep learning present another challenge because training deep models requires high-performance hardware, making it inaccessible in low-resource settings. Optimizing computational efficiency through model compression techniques and energy-efficient training algorithms is an ongoing research priority. Additionally, ethical and security concerns are growing as deep learning integrates into critical sectors. Issues such as biased algorithms, data privacy risks, and potential misuse necessitate stronger regulatory frameworks and explainable AI approaches to ensure transparency and fairness in model decision-making. These concerns are central to the future of deep learning, shaping how it evolves to meet the demands of real-world applications (Shujaat *et al*., 2025).

4. CONCLUSION

Deep learning continues to redefine artificial intelligence by enabling breakthroughs in diverse applications, from healthcare and security to autonomous systems and natural language processing. Its evolution from simple neural networks to sophisticated deep

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

learning architectures has driven significant improvements in pattern recognition, decision-making, and automation. However, this rapid advancement comes with challenges that require strategic solutions. One of the most pressing concerns is the dependency on large, well-annotated datasets, which remains a bottleneck in domains where data is scarce or expensive to obtain. Future research should prioritize techniques such as transfer learning, self-supervised learning, and data-efficient neural architectures to mitigate this limitation. Additionally, optimizing computational efficiency remains critical because deep learning models demand extensive processing power, limiting their accessibility in resource-constrained environments. Innovations in hardware acceleration, quantum computing, and edge AI can address these constraints, making deep learning more scalable and sustainable. Model interpretability and security also present significant challenges because deep neural networks often function as "black boxes," making it difficult to understand their decision-making processes. Enhancing model transparency through explainable AI (XAI) will be crucial for fostering trust in deep learning applications, particularly in high-stakes areas such as medical diagnostics and autonomous decision-making. Similarly, improving adversarial robustness is necessary to safeguard AI systems against manipulation and vulnerabilities. Ethical considerations must also be at the forefront of deep learning research and deployment. Addressing biases in AI models, ensuring fairness, and developing regulations for responsible AI use are essential steps toward mitigating unintended societal consequences. As deep learning technologies become more embedded in everyday life, interdisciplinary collaboration between AI researchers, policymakers, and industry leaders will be key to ensuring their ethical and equitable application. Ultimately, deep learning's future lies in balancing innovation with responsibility. By advancing efficiency, security, and interpretability while maintaining ethical integrity, deep learning can continue to drive technological progress and positively impact society.

5. ACKNOWLEDGMENT

Nulla aliquet facilisis dignissim. Integer quis justo at mauris blandit viverra id at neque. Nunc sed consectetur nisi. Praesent dictum feugiat cursus.

6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. Authors confirmed that the paper was free of plagiarism.

7. REFERENCES

Aggarwal, K., Mijwil, M. M., Al-Mistarehi, A. H., Alomari, S., Gök, M., Alaabdin, A. M. Z., and Abdulrhman, S. H. (2022). Has the future started? The current growth of artificial intelligence, machine learning, and deep learning. *Iraqi Journal for Computer Science and Mathematics*, *3*(1), 115-123.

Aizat, M., Qistina, N., and Rahiman, W. (2023). A comprehensive review of recent advances in automated guided vehicle technologies: Dynamic obstacle avoidance in complex environment toward autonomous capability. *IEEE Transactions on Instrumentation and Measurement*, *73*, 1-25.

Albahar, M. (2023). A survey on deep learning and its impact on agriculture: challenges and opportunities. *Agriculture*, *13*(3), 540.

Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., Asari, V. K. (2019). A state-of-the-art survey on deep learning theory and architectures. *Electronics*, *8*(3), 292.

Archana, R., and Jeevaraj, P. E. (2024). Deep learning models for digital image processing: a review. *Artificial Intelligence Review*, *57*(1), 11.

Chen, X., Wang, X., Zhang, K., Fung, K. M., Thai, T. C., Moore, K., and Qiu, Y. (2022). Recent advances and clinical applications of deep learning in medical image analysis. *Medical Image Analysis*, *79*, 102444.

Cheng, L., Gu, Y., Liu, Q., Yang, L., Liu, C., and Wang, Y. (2024). Advancements in accelerating deep neural network inference on AIoT devices: A survey. *IEEE Transactions on Sustainable Computing*, *9*(6), 830-847.

Ching, T., Himmelstein, D. S., Beaulieu-Jones, B. K., Kalinin, A. A., Do, B. T., Way, G. P., and Greene, C. S. (2018). Opportunities and obstacles for deep learning in biology and medicine. *Journal of The Royal Society Interface*, *15*(141), 20170387.

Choudhary, K., DeCost, B., Chen, C., Jain, A., Tavazza, F., Cohn, R., and Wolverton, C. (2022). Recent advances and applications of deep learning methods in materials science. *Computational Materials*, *8*(1), 59.

Dasgupta, S., Wörgötter, F., and Manoonpong, P. (2013). Information dynamics based self-adaptive reservoir for delay temporal memory tasks. *Evolving Systems*, *4*, 235-249.

Di, X., Shi, R., Mo, Z., and Fu, Y. (2023). Physics-informed deep learning for traffic state estimation: A survey and the outlook. *Algorithms*, *16*(6), 305.

Fort, S., Dziugaite, G. K., Paul, M., Kharaghani, S., Roy, D. M., and Ganguli, S. (2020). Deep learning versus kernel learning: an empirical study of loss landscape geometry and the time evolution of the neural tangent kernel. *Advances in Neural Information Processing Systems*, *33*, 5850-5861.

Fuad, M. T. H., Fime, A. A., Sikder, D., Iftee, M. A. R., Rabbi, J., Al-Rakhami, M. S., and Islam, M. N. (2021). Recent advances in deep learning techniques for face recognition. *IEEE Access*, *9*, 99112-99142.

Javed, H., El-Sappagh, S., and Abuhmed, T. (2025). Robustness in deep learning models for medical diagnostics: security and adversarial challenges towards robust AI applications. *Artificial Intelligence Review*, *58*(1), 1-107.

Kandathil, S. M., Greener, J. G., and Jones, D. T. (2019). Recent developments in deep learning applied to protein structure prediction. *Proteins: Structure, Function, and Bioinformatics*, *87*(12), 1179-1189.

Kitchenham, B., Brereton, O. P., Budgen, D., Turner, M., Bailey, J., and Linkman, S. (2009). Systematic literature reviews in software engineering–a systematic literature review. *Information and Software Technology*, *51*(1), 7-15.

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860

Latendresse, J., Abedu, S., Abdellatif, A., and Shihab, E. (2024). An exploratory study on machine learning model management. *ACM Transactions on Software Engineering and Methodology*, *34*(1), 1-31.

Lee, M. (2023). The geometry of feature space in deep learning models: A holistic perspective and comprehensive review. *Mathematics*, *11*(10), 2375.

Li, Z., Shi, N., Zhao, L., and Zhang, M. (2024). Deep reinforcement learning path planning and task allocation for multi-robot collaboration. *Alexandria Engineering Journal*, *109*, 408-423.

Manakitsa, N., Maraslidis, G. S., Moysis, L., and Fragulis, G. F. (2024). A review of machine learning and deep learning for object detection, semantic segmentation, and human action recognition in machine and robotic vision. *Technologies*, *12*(2), 15.

Martín, A., and Camacho, D. (2022). Recent advances on effective and efficient deep learning-based solutions. *Neural Computing and Applications*, *34*(13), 10205-10210.

Mishra, C., and Gupta, D. L. (2016). Deep machine learning and neural networks: an overview. *International Journal Hybrid Information and Technology*, *9*(11), 401-414.

Najjar, R. (2023). Redefining radiology: A review of artificial intelligence integration in medical imaging. *Diagnostics*, *13*(17), 2760.

Pantoja, M., Behrouzi, A. A., and Fabris, D. (2018). An introduction to deep learning. *Concrete International*, *40*(9), 35-41.

Pati, D., and Lorusso, L. N. (2018). How to write a systematic review of the literature. *HERD: Health Environments Research & Design Journal*, *11*(1), 15-30.

Rane, C., Tyagi, K., Kline, A., Chugh, T., and Manry, M. (2024). Optimizing performance of feedforward and convolutional neural networks through dynamic activation functions. *Evolutionary Intelligence*, *17*(5), 4083-4093.

Rane, N. L., Paramesha, M., Choudhary, S. P., and Rane, J. (2024). Machine learning and deep learning for big data analytics: A review of methods and applications. *Partners Universal International Innovation Journal*, *2*(3), 172-197.

Ribeiro, H. V., Lopes, D. D., Pessa, A. A., Martins, A. F., Da Cunha, B. R., Gonçalves, S., and Perc, M. (2023). Deep learning criminal networks. *Chaos, Solitons & Fractals*, *172*, 113579.

Sapoval, N., Aghazadeh, A., Nute, M. G., Antunes, D. A., Balaji, A., Baraniuk, R., and Treangen, T. J. (2022). Current progress and open challenges for applying deep learning across the biosciences. *Nature Communications*, *13*(1), 1728.

Shujaat, S. (2025). Automated machine learning in dentistry: A narrative review of applications, challenges, and future directions. *Diagnostics*, *15*(3), 273.

Van Dinter, R., Tekinerdogan, B., and Catal, C. (2021). Automation of systematic literature reviews: A systematic literature review. *Information and software technology*, *136*, 106589.

Wang, S., Dong, Z., Zhang, Z., Huo, Y., Celebi, M. E., and Shan, C. (2022). Guest editorial emerging challenges for deep learning. *IEEE Journal of Biomedical and Health Informatics*, *26*(11), 5287-5288.

Wong, A., Bäck, T., Kononova, A. V., and Plaat, A. (2023). Deep multiagent reinforcement learning: Challenges and directions. *Artificial Intelligence Review*, *56*(6), 5023-5056.

Xu, P., Zhu, X., and Clifton, D. A. (2023). Multimodal learning with transformers: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *45*(10), 12113-12132.

Yang, Y. (2023). Current trends in deep learning. *Advances in Engineering Technology Research*, *5*(1), 422-422.

Zhang, T., and Mo, H. (2021). Reinforcement learning for robot research: A comprehensive review and open issues. *International Journal of Advanced Robotic Systems*, *18*(3), 17298814211007305.

Zhou, X., Wang, H., Feng, C., Xu, R., He, Y., Li, L., and Tu, C. (2022). Emerging applications of deep learning in bone tumors: current advances and challenges. *Frontiers in oncology*, *12*, 908873.

DOI:
p- ISSN: 2828-4887 e- ISSN: 2828-4860