



Neural Networks in Electrical Engineering Applications: A Review

Fawad Khan^{1*}

¹Trine University, USA

Fawadkhank313@gmail.com



Corresponding Author

Fawad Khan

Fawadkhank313@gmail.com

Article History:

Submitted: 15-03-2026

Accepted: 25-04-2026

Published: 29-04-2026

Keywords

Neural networks, electrical engineering, power systems, control systems, machine learning, deep learning, renewable energy.

Global Trends in Science and Technology is licensed under a Creative Commons Attribution-Noncommercial 4.0 International (CC BY-NC 4.0).

ABSTRACT

Neural networks are an essential component of electrical engineering, as they can model nonlinear, complex and data-driven systems. Here, we review their use in power systems, control systems, electrical machines, power electronics and smart grids. They enhance load prediction, fault diagnosis, stability, motor control and energy management, as well as efficiency and reliability. New techniques like deep learning and hybrid models enhance their use. While facing issues such as data requirements and interpretability, research is making progress. In summary, neural networks play a significant role in creating smart, adaptable and efficient electrical engineering systems.

INTRODUCTION

Neural networks are a significant computational approach in engineering, in particular, electrical engineering. Artificial neural networks (ANNs) are inspired by the human brain, and can learn patterns, model non-linearity, and make intelligent decisions based on data. Over the past few decades, their applications have expanded rapidly due to the ever-increasing computing capability, big data, and the increasing complexity in electrical engineering systems [1]. Electrical engineering systems (e.g. power systems, electrical machines, control systems, electrical converters) are complex, nonlinear and may operate in uncertain or changing environments [2].

Traditional mathematical modelling approaches are often successful, they may not always be able to accurately represent the behavior of these systems in real-time or under various operating conditions.





As a result, there is a need for intelligent systems, such as neural networks, which have proven to be effective. Neural networks have a number of attributes that make them attractive to electrical engineers [3]. They have good approximation properties, enabling them to model complex and nonlinear relationships without knowing their mathematical formulas. They can also learn through experience, both from data and online, and are adaptive and robust [4]. Such characteristics are useful for many applications in electrical engineering such as fault detection in electrical power systems, load prediction, control of electrical drives and design of power electronics systems [5].

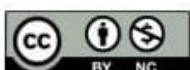
The application of neural networks in electrical engineering has also been pushed by the advances in machine learning and artificial intelligence. Specifically, deep learning, a type of neural networks, has enhanced the ability to process large amounts of data and automatically extract features. This provides new possibilities in smart grids, renewable energy integration, predictive maintenance and smart automation [6]. Neural networks have several advantages but also some limitations, including the requirement for large training data sets, computational power and lack of interpretability. But new research is addressing these issues, including hybrid models, training methods and hardware acceleration [7].

Neural networks in electrical engineering is a significant leap towards intelligent, adaptive systems. Their ability to learn, capture complex non-linear patterns and operate in a dynamic environment make them well-suited to modern engineering challenges. As electrical systems become more sophisticated and there is a growing integration of renewable energy, the application of neural networks for improving efficiency, reliability and automation of systems will only become more significant. This opens up opportunities for future research and development in smart electrical engineering.

BASICS OF NEURAL NETWORKS

Neural networks are mathematical models of the biological neural system (the human brain). They are systems of interconnected processing units or neurons that work together to perform tasks by learning or approximating functions that best map the inputs to the desired outputs. In order to appreciate the use of neural networks in electrical engineering, let's first look into the fundamentals of neural networks [8].

Biological Inspiration: Neural networks are based on biological neural communication and processing. Biological neurons are interconnected to synapses, which are responsible for receiving, processing and sending signals. Similarly, artificial neurons acquire input signals, multiply with weights, process and then generate an output. The above analogy is used to build artificial neural networks that enable computers to mimic learning and decision-making [9].





Structure of Artificial Neural Network: An artificial neural network consists of three layers: input, hidden and output. The input layer receives input from the physical world, such as voltage, current, temperature and other electrical variables in engineering applications. The hidden layers are intermediate layers which learn to identify features and patterns using weights and activation functions [10]. The output layer produces the output, which can be classification, prediction or control. The influence of the input to the neuron is determined by weights. Weights are then adjusted to minimize the error. The activation functions such as sigmoid, ReLU (Rectified Linear Unit) and tanh introduce non-linearity so that neural networks are able to learn and capture the complex and non-linear interactions in electrical engineering systems [11].

Learning Algorithms: Neural networks learn through algorithms which modify the weights of the network according to the data inputs and desired outputs. The most common type of learning is supervised learning, where the network is presented with input data along with the expected output. Back propagation is frequently used in this case, back propagating the errors to update the weights, which is often done using an optimization technique like gradient descent [12].

Other learning paradigms include unsupervised learning (no labels) and reinforcement learning (learning through rewards and punishments). These approaches enable neural networks to be used for several electrical engineering applications, such as system identification and control [13]. The principles of neural networks are biologically inspired, have a structure and use learning algorithms. These enable their modeling, prediction and decision-making capabilities, and render them very useful in electrical engineering [14].

OVERVIEW OF ELECTRICAL ENGINEERING APPLICATIONS

Electrical engineering is a multidisciplinary and ever-evolving field that encompasses the analysis, design, development and maintenance of electrical systems and technologies. It covers various areas such as power systems, electrical machines, and control systems, signal processing and power electronics. Over the past few decades, the growing complexity of these systems, along with the desire for increased efficiency, reliability, and automation, has resulted in the adoption of modern computational methods such as neural networks [15].

A key feature of contemporary electrical engineering systems is the presence of nonlinearity, uncertainty and time-varying properties. Such behavior is difficult to capture effectively by conventional analytical and mathematical techniques, particularly in real-time systems. For example, power systems are impacted by varying loads, faults and renewable energy source integration and electrical machines are subjected to varying mechanical and electrical conditions [16]. These issues have led to the need for smart and adaptive approaches.



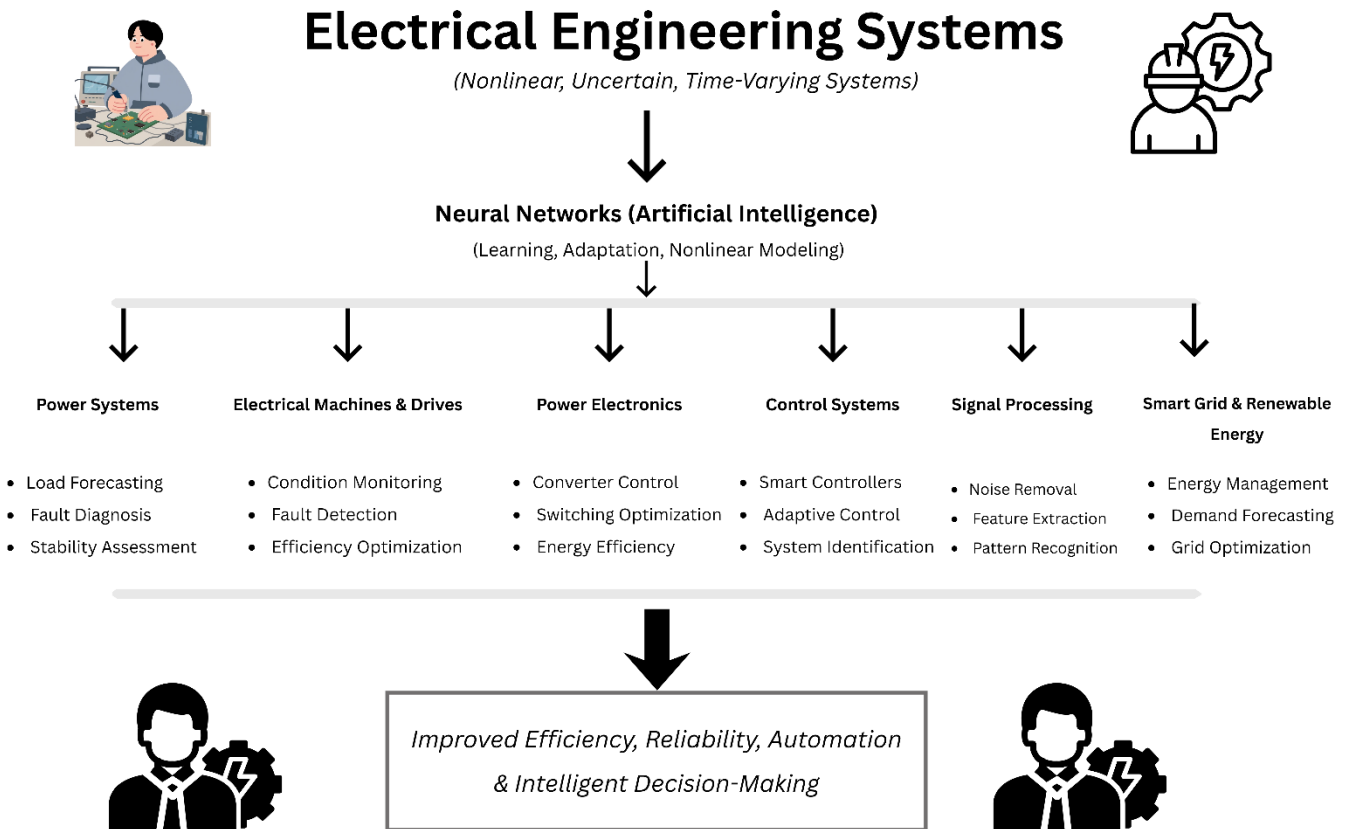


Figure 1. Electrical Engineering Systems

Neural networks are a significant solution for these problems because they have the capacity to learn from data and model arbitrary nonlinear functions. Neural networks are increasingly being employed in electrical engineering for prediction, classification, optimization and control [17]. Neural networks are well-suited for systems with a high volume of data and where traditional modeling methods are inadequate or overly rigid. Neural networks are used in power systems for load prediction, fault diagnosis, stability assessment and optimal power flow. For instance, precise load forecasting is crucial for power generation and distribution, and neural networks offer better performance than statistical approaches. Likewise, for fault detection and diagnosis, they rapidly detect anomalies, enhancing reliability and avoiding breakdowns [18].

In electrical machines and drives, neural networks are applied for condition monitoring, fault diagnosis and optimization of performance. They help with motor fault prediction, efficiency improvement and control. Neural networks in power electronics are used to improve the performance of converters, switch control, and efficiency of energy conversion devices [19]. Neural networks also play a vital role in control systems. Neural network-based smart controllers can learn system dynamics and offer superior performance over traditional PID controllers in complex systems. Moreover, neural networks are applied in signal processing for noise removal, feature extraction and



pattern recognition, crucial components in communication and measurement systems [20].

As smart grids and renewable energy sources are being developed, neural networks are increasingly being used for distributed energy resource management, energy demand forecasting, and grid optimization. Their ability to adapt and learn is crucial for the development of smarter and automated electrical systems the use of neural networks in electrical engineering is a departure from traditional deterministic models to intelligent systems that learn from data, delivering more efficient, reliable and adaptive engineering solutions [21].

NEURAL NETWORKS IN POWER SYSTEMS

Electrical power systems are one of the most important and challenging areas within electrical engineering, involving the generation, transmission, distribution and consumption of electric energy. Power systems are large scale, highly nonlinear and subject to variable operational conditions, including demand, faults and the integration of new generation sources such as renewables [22]. This makes it difficult for traditional analytical and rule-based techniques to provide accurate, fast and adaptive control. Neural networks have thus become a promising technique for enhancing the efficiency, reliability, and smartness of the power system [23].

Load forecasting is a key area where neural networks can play a vital role in power systems. Load forecasting is crucial for optimal generation planning, energy management, and cost minimization. Neural networks can learn from past load patterns and other factors including weather, time of day, and seasonality to accurately forecast future load [24]. Neural network-based load forecasting models can capture non-linear relationships and other complex patterns in data more accurately than conventional statistical methods, and are very effective for short-term, medium-term and long-term load forecasting [25].

The second major usage of neural networks is fault detection and diagnosis. Power systems are prone to a range of faults, such as short circuits, line outages and equipment failures. Timely detection and diagnosis of these faults is essential to avoid system instability and damage. Neural networks can be trained with fault data to detect irregularities in voltage, current and frequency [26]. They can then rapidly identify the type of fault, and even the fault location, enhancing system protection and minimising downtime.

Neural networks are also extensively applied in power system stability analysis and control. Dynamic stability is a critical issue in large power systems. Neural networks can be used to model system dynamics and forecast the onset of instability. Neural networks are also employed in developing smart controllers to dynamically modify system parameters to ensure voltage stability, frequency stability and system balance. This feature is especially important in systems with high renewable generation,



given the intermittent nature of the generation [27].

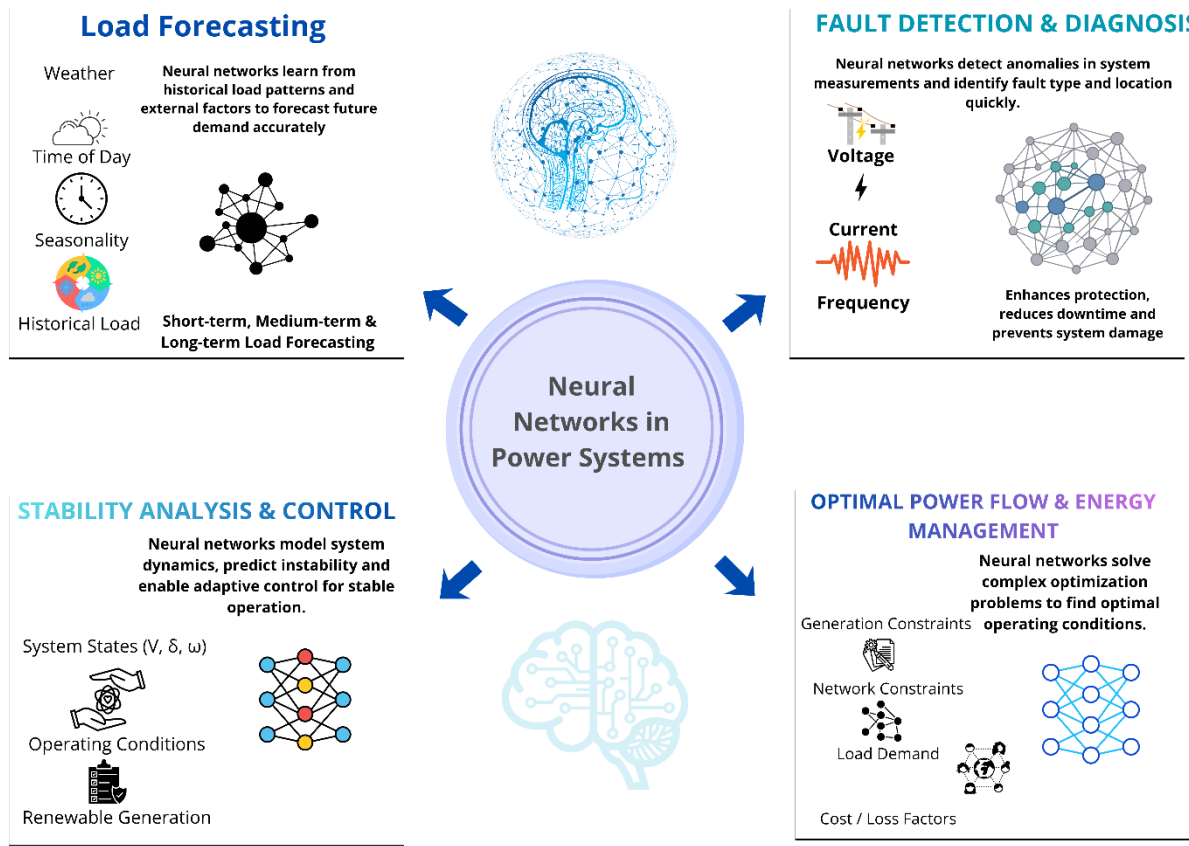


Figure 2. Neural Networks in Power Systems

Neural networks are also used for optimal power flow (OPF) and energy management. They help to identify the optimum conditions for power generation and transmission to reduce losses and costs. Their capability to deal with multiple variables and constraints makes them ideal for solving complex optimization problems of power systems [28]. In the era of smart grids, neural networks are even more crucial in providing real-time monitoring, demand response, and distributed energy resource integration. They assist utilities in decision making, increasing energy efficiency and reliability. Neural networks have revolutionized power system engineering by offering sophisticated methods for prediction, diagnosis, control and optimization [29]. Their flexibility, learning ability and efficiency make them essential for today and the future of power systems.

NEURAL NETWORKS IN CONTROL SYSTEMS

Control systems are a cornerstone of electrical engineering applications, used to control the dynamics of systems to achieve a desired level of performance. They are commonly applied in industrial processes, robots, power systems, electric drives, and process control. Classical control methods like proportional-integral-derivative (PID) control, state-space control, and feedback control have been successful in linear and well-understood systems [30]. But many systems are nonlinear, time-varying



and uncertain, for which traditional methods may not work well. Neural networks offer a promising solution through data-driven, adaptive and intelligent control [31].

A key area where neural networks can be used in control systems is adaptive control. Neural network-based adaptive controllers can dynamically update their parameters based on the system's performance. This capability enables them to cope with nonlinearities and varying operating conditions. For instance, in manufacturing applications with variable loads or system dynamics, neural networks can adaptively learn the system dynamics and adjust the control actions accordingly [32].

Another major use is in the design of smart controllers, such as neural-network-based PID controllers. In conventional PID control, tuning parameters of the controller can be challenging and often involves manual tuning or tuning by trial and error. Neural networks can learn the best PID controller parameters from the system's data. This leads to faster response, overshoot reduction and better stability [33]. These controllers are particularly valuable in applications such as robotic manipulators, motor drives and chemical process control.

Neural networks are also popular choices for system identification, where the goal is to model the dynamics of an unknown or partially known dynamic system. Neural networks can learn system dynamics from input-output data to build accurate system models without knowing the underlying physical equations [34]. This is a critical aspect of control system design, as models are needed to predict system behavior and develop control strategies. Neural networks play a role in nonlinear control, which is not possible with conventional linear control approaches. Electrical engineering systems like DC motors, AC drives and power converters are often nonlinear. Neural networks can model these nonlinearities and generate control actions to maintain stable operation under various operating conditions [35].

Another significant application is fault-tolerant control systems, where neural networks assist in maintaining system stability and performance despite faults or anomalies. Neural networks improve system safety and reliability by detecting faults and adjusting control strategies. This is crucial for aerospace, power generation, and manufacturing industries [36]. As artificial intelligence technology evolves, neural networks are also combined with other approaches like fuzzy logic and genetic algorithms to create hybrid control systems. This approach leverages the learning capability of neural networks with rule-based systems to create more effective controllers [37]. Neural networks have revolutionised control systems in electrical engineering by allowing adaptive, smart and nonlinear control. Their learning capability and adaptability to the environment make them extremely useful in engineering practice [38].



NEURAL NETWORKS IN ELECTRICAL MACHINES AND DRIVES

Electrical machines and drives are a fundamental component of electrical engineering applications, and are essential to industrial automation, transportation, and robotics and energy conversion. Such systems comprise of motors, generators and drive systems for converting electrical energy to mechanical energy and vice versa [39]. Electrical machines often face nonlinear, time-varying, and uncertain operating conditions in practical applications, due to load variations, parameter uncertainties, temperature variations and degradation. Conventional control and monitoring methods may not always offer the desired accuracy or flexibility in these complicated scenarios. As a result, neural networks have been used to enhance the performance, reliability and efficiency in this field [40].

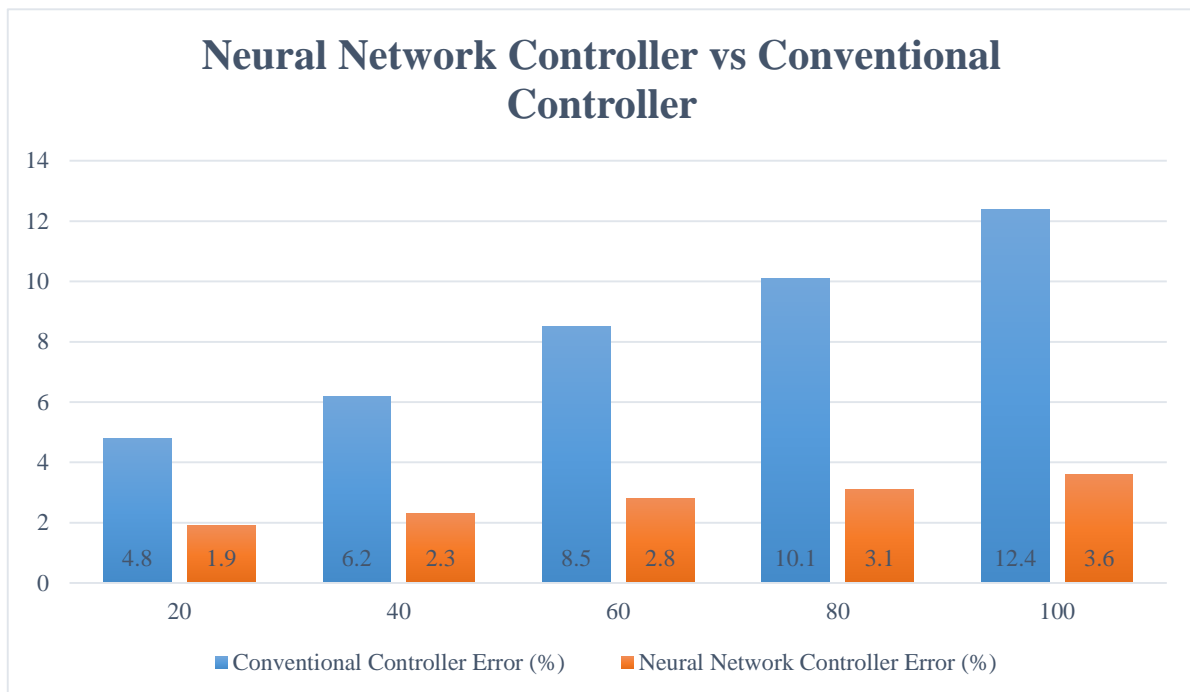


Figure 3. Neural Network Controller vs Conventional Controller

A key area in which neural networks are used in electrical machines and drives is motor control and optimization. Electrical motors (including induction motors, synchronous motors and DC motors) need to be controlled for speed, torque and position. Neural networks can be trained to model the complex relationship between the input commands (voltage and current) and output performance (speed and torque) [41]. This enables them to produce control signals to optimise dynamic performance, power efficiency, and efficiency. Neural network-based controllers are often superior to traditional controllers as they can adapt to varying load conditions [42].

Condition monitoring and fault prediction is another important application. Electrical machines can develop faults such as bearing damage, stator winding faults, rotor bar faults and insulation faults. It's



important to detect these faults early on to avoid sudden failures and costly repairs. Neural networks can process vibration, current, temperature and acoustic measurements to detect unusual patterns that indicate the presence of a fault [43]. With proper training, they can not only identify fault types, but also assess the damage level, allowing predictive maintenance to enhance reliability and prevent system downtime.

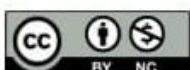
Neural networks also play a role in parameter estimation and system identification of electrical machines. Some machine parameters, such as resistance, inductance and flux linkage, can vary and are hard to measure. Neural networks can be used to accurately estimate these parameters using measured data to enhance system control and modeling [44]. They are also widely used in adaptive and sensorless control of drives. Sensorless control methods avoid the use of sensors by estimating quantities like rotor speed and position with neural networks. This lowers the system cost, makes it more robust, and more reliable, particularly in some industrial settings where sensors can wear out or malfunction [45].

Neural networks are also now often combined with advanced drive systems for electric vehicles, robotics, and renewable energy systems. For instance, in electric vehicles, they are used to improve motor efficiency, battery management and regenerative braking. Neural networks have brought much-needed intelligence, fault diagnosis and performance optimization to the world of electrical machines and drives [46]. Neural networks' adaptability and capacity to model nonlinear system dynamics make them a vital component of contemporary and future drive systems.

APPLICATIONS IN POWER ELECTRONICS

Power electronics is an important field of electrical engineering focused on the control and conversion of electrical power using electronic devices. This involves rectifiers, inverters, DC-DC and AC-AC converters, and is used in industrial drives, renewable energy, electric vehicles and power supply units. They are highly dynamic, nonlinear, and operate under varying conditions [47]. This makes it difficult to achieve high efficiency, stability, and dynamic response with traditional control techniques. Neural networks have recently been used as an effective means to tackle these problems by incorporating smart, adaptive, and data-driven control techniques [48].

A key application of neural networks in power electronics is the control and optimization of converters. Power converters need to control voltage and current levels with minimal losses and ensure stability. Neural networks can adapt to the nonlinear switching characteristics of converters and produce control signals. This helps achieve better voltage regulation, lower harmonic distortion and faster transient response [49]. For instance, neural networks can dynamically control the duty cycle in DC-DC converters to keep the output voltage stable under changing input voltage or load.





A key area is the control of inverters, particularly in motor drives and renewable energy systems [50]. Inverters are used to convert DC to AC power, and their efficiency and effectiveness impact overall system performance and power quality. Neural networks help in adjusting pulse width modulation (PWM), minimising switching losses and improving the waveform. They are also used to minimise total harmonic distortion (THD) to ensure power quality in sensitive electrical systems [51].

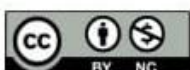
Neural networks are also commonly used for harmonic analysis and compensation. Harmonics can be introduced into electrical systems by power electronic devices, affecting efficiency and causing equipment failure. Neural networks can be used to monitor the voltage and current waveforms and identify harmonics, producing compensating signals [52]. This helps enhance system efficiency and meet power quality standards. Neural networks are also used for fault detection and diagnosis in power electronic systems. Elements like IGBTs, MOSFETs and diodes can malfunction due to thermal effects, overvoltage, and switching problems [53]. Neural networks can analyse electrical signals to detect signs of component wear or breakdown. This allows for proactive maintenance, enhancing efficiency and reliability.

A recent advancement is the use of neural networks for power electronic systems powered by renewable energy sources, such as solar photovoltaic (PV) inverters and wind energy converters. These converters need effective maximum power point tracking (MPPT) techniques to harvest energy under different environmental conditions. Neural networks excel at estimating the optimum operating point and rapidly responding to variations in solar radiation or wind power [54].

Moreover, neural networks are also integrated with other control techniques like fuzzy control and model predictive control to develop intelligent control systems. These controllers provide enhanced stability, flexibility and efficiency in challenging power electronic systems. Neural networks have boosted the performance of power electronics in terms of efficiency, harmonic reduction, intelligent control and reliability. Neural networks are highly sought after in power electronic systems for their capability to learn nonlinear functions and adapt to changing conditions [55].

CHALLENGES AND LIMITATIONS

Although neural networks are widely used and perform well in many electrical engineering applications, there are also some challenges and limitations associated with their use. These can impact their accuracy, explainability, and suitability for practical engineering applications like power systems, control and electrical machines. Large amounts of data are needed [56]. Neural networks require large amounts of good quality data for training. In electrical engineering problems, particularly during rare events such as faults, this data can be scarce. The lack of data might result in over fitting, in which the model learns to perform well on training data but not on unseen data [57].





A major challenge is also the computational expense of training neural networks. Deep neural networks, in particular, are computationally intensive and may require significant time to train. This can pose a problem for real-time systems or resource-constrained systems, such as industrial control systems. Another key issue is the lack of interpretability [58]. Neural networks are sometimes referred to as "black boxes" due to the lack of interpretability of their decision-making. In electrical engineering applications, where safety and reliability are paramount, engineers can be reluctant to use models that lack physical insight [59]. Lack of interpretability can lead to reduced confidence in critical applications like power system protection and fault diagnosis.

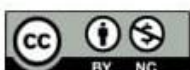
Overfitting is another issue where the model memorises specific details from the training data rather than capturing broader or general patterns. This can lead to poor generalization and accuracy with unseen data. While overfitting can be minimised using methods like regularisation and cross-validation, it is a critical consideration in neural network architecture. Neural networks also require careful tuning and architecture design [60]. The selection of the number of layers, neurons, learning rate and activation functions is often done experimentally. Incorrect choices can lead to poor performance. Moreover, there are issues with real-time implementation and latency. In applications like motor control and power system protection, decisions need to be made in milliseconds [61]. Large or intricate neural network models may take too long to process and may not be feasible in real-time applications without optimisations or dedicated hardware.

Another issue is data sensitivity. Neural networks can be sensitive to noisy, biased, or missing data, which can lead to unreliable results. Hence, data preprocessing and validation is critical. Neural networks may struggle with extreme or rare operating conditions, such as uncommon faults or system disturbances [62]. They rely heavily on past data for training, and may struggle with new or unfamiliar data patterns. Although neural networks provide powerful tools in electrical engineering, data dependency, interpretability, computational complexity, and reliability issues must be considered carefully in the design, hybrid systems, and ongoing research [63].

DEVELOPMENTS AND HYBRID SYSTEMS

Neural networks in electrical engineering have seen rapid development in recent years thanks to increasing computational capabilities, data collection and artificial intelligence research. Existing neural network models, although successful, are being expanded and improved upon using current technologies like deep learning and hybrid intelligent systems. Such recent developments have led to better performance, accuracy and flexibility in neural networks for solving complex electrical engineering problems [64].

A significant advancement is the use of deep learning, a type of neural network with multiple hidden





layers. DNNs can automatically learn hierarchical features from data without the need for feature engineering. Deep learning is a common approach in electrical engineering for fault diagnosis in power systems, visual inspection of electric equipment and machinery, and predictive maintenance [65]. For instance, convolutional neural networks (CNNs) are particularly useful for processing visual information such as thermal images of transformers or circuit boards for fault diagnosis. Likewise, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are employed for time series analysis in load forecasting and signal processing [66].

Another growing trend is the development of hybrid systems, which involve the use of neural networks together with other intelligent technologies to enhance performance and address shortcomings. A popular hybrid system is the fuzzy neural network (FNN), which incorporates the learning power of neural networks with the reasoning power of fuzzy logic systems [67]. This combination is beneficial in applications such as control and decision-making, where imprecision and uncertainty is often present. The fuzzy-ANN system offers better interpretability and uncertainty handling than pure neural networks. There have been neuro-genetic systems that incorporate genetic algorithms to determine the parameters of neural networks, including weights, the number of layers and learning rates. This addresses the issue of manual tuning and enhances convergence rate. These are particularly beneficial for solving optimization problems in power systems and power electronics [68].

There is also a growing interest in reinforcement learning with neural networks, known as deep reinforcement learning (DRL). In the field of electrical engineering, DRL is being used for smart grid control, adaptive control, and energy management. It enables systems to learn control policies by interacting with the environment, and is well suited for uncertain environments. Neural network applications are also being affected by the emergence of edge computing and hardware acceleration [69]. By leveraging the power of GPUs, TPUs, and custom embedded AI chips, neural networks can be applied in real-time scenarios such as smart meters, process automation, and electric vehicles.

In addition, there is growing concern about explainable artificial intelligence (XAI) and making neural network decisions more explicable. This is especially relevant for electrical engineering applications that have safety, reliability, and regulatory concerns [70]. Recent developments in deep learning, hybrid neural networks, reinforcement learning and hardware acceleration have enhanced the usefulness of neural networks in electrical engineering. These developments are enabling systems to become smarter, faster, adaptive and capable of tackling complex engineering challenges [71].





FUTURE SCOPE AND RESEARCH DIRECTIONS

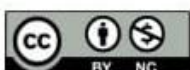
The prospects of neural networks in electrical engineering are bright, as driven by ongoing advancements in artificial intelligence, computing technology and increasing complexity of electrical engineering systems. With increasing interdependence and data-driven nature in power systems, control systems, electrical machines and power electronics, neural networks are likely to play an even more significant role in facilitating smart, adaptive and efficient operations [72].

A key focus for the future is more interpretable neural networks. A major drawback of neural networks to date is their "black box" nature, where reasoning is not transparent. For critical electrical engineering applications like power system protection, fault detection and industrial automation, engineers need to understand the reasoning behind decisions [73]. The next frontier of research in explainable artificial intelligence (XAI) will be making neural network models more interpretable while maintaining accuracy, and thus increasing the confidence and applicability of safety-critical systems.

Another future research focus is on edge intelligence and real-time embedded neural networks. The ever-increasing deployments of smart grids, electric vehicles, and industrial IoT systems demand rapid, energy efficient, and real-time decision-making. Neural network models of the future will be run on edge devices with dedicated hardware like GPUs, TPUs and xeromorphic chips [74]. This will allow for local processing, monitoring and fault detection in real time, thereby reducing the response time and increasing the reliability of the system. Neural networks will also be increasingly integrated with renewable energy sources and smart grids [75]. The increasing role of renewable energy will continue to pose challenges in dealing with variability and uncertainty. Neural network models will aim to enhance energy prediction, energy storage and self-managing grids. This will help in the shift towards intelligent and self-healing networks [76].

Hybrid intelligent systems, which integrate neural networks with other advanced methods like fuzzy logic, evolutionary algorithms, swarm intelligence and physics-based models, are another important research direction. Hybrid systems seek to integrate the learning capability of neural networks with expert knowledge and optimization techniques, to provide more effective and efficient solutions to complex electrical engineering challenges [77].

Deep reinforcement learning (DRL) is also likely to play a crucial role in future applications. DRL systems can learn how to control complex systems through interaction with the environment, making them well-adapted for control applications in power systems, robotics and energy management. Future studies will aim to enhance the efficiency of data and learning from small data sets, as large volumes of high-quality labeled data are not always available in electrical engineering applications





[78]. Transfer learning, few-shot learning, and self-supervised learning will be critical to this end. The pairing of neural networks with cyber-physical systems and Industry 4.0 technologies will result in highly autonomous, smart and connected electrical systems. This will result in predictive maintenance, autonomous control, and large-scale system optimization. The future of neural networks in electrical engineering will involve more intelligence, efficiency, interpretability, and adaptability, and will be a key element of future engineering systems [79].

CONCLUSION

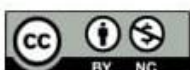
Neural networks have proven to be a game-changing technology in electrical engineering, dramatically changing the way systems are modeled, analysed, controlled and optimised. In every major subfield of electrical engineering - power systems, control systems, electrical machines and power electronics, signal processing and smart grid integration - neural networks have shown tremendous potential to deal with nonlinearities, uncertainties and data-driven decision-making challenges that conventional techniques struggle to tackle. Their capacity to learn and adapt has made them a critical tool in modern and future electrical engineering.

For instance, in power systems, neural networks have been used to enhance load forecasting, fault detection and diagnosis, and stability analysis and optimal power flow control. This is essential for efficient and reliable operation of large electrical systems, particularly with growing renewable energy integration. Likewise, in control systems, neural networks have facilitated intelligent control techniques that adapt to changing conditions and perform better than fixed-parameter controllers. Their applications in system identification and nonlinear control have also solidified their significance in automation and robotics.

Neural networks have also made a significant impact on electrical machines and drives. These have led to better motor control, fault diagnosis, health monitoring, and sensorless operation, which have improved system performance, reliability and cost-effectiveness. For power electronics, neural networks have helped to enhance the performance of converters and inverters, lower harmonic content, and detect faults, all of which are crucial for efficient power conversion applications.

The use of neural networks in smart grids and renewable energy systems is a major breakthrough in electrical engineering. Neural networks are facilitating the shift towards smarter, cleaner and more resilient energy systems through forecasting, demand response, renewable energy forecasting, and system monitoring. Their capacity to handle big data, and deliver adaptive solutions, is key to managing the complexity of future grids.

However, neural networks also have drawbacks such as data-intensive, computational-intensive, lack of explain ability, and sensitivity to tuning. But recent advancements in deep learning, hybrid





intelligent systems, explainable AI and edge computing are constantly overcoming these challenges. New techniques such as fuzzy-neural systems, reinforcement learning, and physics-informed neural networks also continue to enhance their potential and applications.

The prospects of neural networks in electrical engineering are exciting. Thanks to improved hardware, algorithms and data sets, neural networks are likely to be more efficient, interpretable, and accessible for real-time and safety-critical applications. Their application with smart technologies, cyber-physical systems and Industry 4.0 will result in more autonomous, intelligent and efficient electrical engineering systems. Neural networks are a powerful tool that integrates complex physical processes and smart computing. Their ongoing evolution and adoption in electrical engineering will be essential in the development of future energy systems, automation and smart systems globally.

REFERENCES

- [1]. Shehab M, Abualigah L, Omari M, Shambour MK, Alshinwan M, Abuaddous HY, Khasawneh AM. Artificial neural networks for engineering applications: a review. *Artificial neural networks for renewable energy systems and real-world applications*. 2022 Jan 1:189-206.
- [2]. Abiodun OI, Jantan A, Omolara AE, Dada KV, Umar AM, Linus OU, Arshad H, Kazaure AA, Gana U, Kiru MU. Comprehensive review of artificial neural network applications to pattern recognition. *IEEE access*. 2019 Oct 4;7:158820-46.
- [3]. Mohd Amiruddin AA, Zabiri H, Taqvi SA, Tufa LD. Neural network applications in fault diagnosis and detection: an overview of implementations in engineering-related systems. *Neural Computing and Applications*. 2020 Jan;32(2):447-72.
- [4]. Abiodun OI, Jantan A, Omolara AE, Dada KV, Mohamed NA, Arshad H. State-of-the-art in artificial neural network applications: A survey. *Heliyon*. 2018 Nov 1;4(11).
- [5]. Moayedi H, Mosallanezhad M, Rashid AS, Jusoh WA, Muazu MA. A systematic review and meta-analysis of artificial neural network application in geotechnical engineering: theory and applications. *Neural Computing and Applications*. 2020 Jan;32(2):495-518.
- [6]. Yamazaki K, Vo-Ho VK, Bulsara D, Le N. Spiking neural networks and their applications: A review. *Brain sciences*. 2022 Jun 30;12(7):863.
- [7]. Wang X, Lu H, Wei X, Wei G, Behbahani SS, Iseley T. Application of artificial neural network in tunnel engineering: a systematic review. *IEEE Access*. 2020 Jun 25;8:119527-43.
- [8]. Abdolrasol MG, Hussain SS, Ustun TS, Sarker MR, Hannan MA, Mohamed R, Ali JA, Mekhilef S, Milad A. Artificial neural networks based optimization techniques: A review. *Electronics*. 2021 Nov 3;10(21):2689.



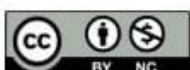


- [9]. Chien E, Li M, Aportela A, Ding K, Jia S, Maji S, Zhao Z, Duarte J, Fung V, Hao C, Luo Y. Opportunities and challenges of graph neural networks in electrical engineering. *Nature reviews electrical engineering*. 2024 Aug;1(8):529-46.
- [10]. Paul AK, Prasad A, Kumar A. Review on artificial neural network and its application in the field of engineering. *J. Mech. Eng. Prakash*. 2022;1(1):53-61.
- [11]. Ozcanli AK, Yaprakdal F, Baysal M. Deep learning methods and applications for electrical power systems: A comprehensive review. *International Journal of Energy Research*. 2020 Jul;44(9):7136-57.
- [12]. Yousuf H, Lahzi M, Salloum SA, Shaalan K. A systematic review on sequence-to-sequence learning with neural network and its models. *International Journal of Electrical and Computer Engineering*. 2021 Jun 1;11(3):2315.
- [13]. Samek W, Montavon G, Lapuschkin S, Anders CJ, Müller KR. Explaining deep neural networks and beyond: A review of methods and applications. *Proceedings of the IEEE*. 2021 Mar 4;109(3):247-78.
- [14]. Liao W, Bak-Jensen B, Pillai JR, Wang Y, Wang Y. A review of graph neural networks and their applications in power systems. *Journal of Modern Power Systems and Clean Energy*. 2021 Aug 20;10(2):345-60.
- [15]. Liao W, Bak-Jensen B, Pillai JR, Wang Y, Wang Y. A review of graph neural networks and their applications in power systems. *Journal of Modern Power Systems and Clean Energy*. 2021 Aug 20;10(2):345-60.
- [16]. Wazirali R, Yaghoubi E, Abujazar MS, Ahmad R, Vakili AH. State-of-the-art review on energy and load forecasting in microgrids using artificial neural networks, machine learning, and deep learning techniques. *Electric power systems research*. 2023 Dec 1;225:109792.
- [17]. Han Y, Huang G, Song S, Yang L, Wang H, Wang Y. Dynamic neural networks: A survey. *IEEE transactions on pattern analysis and machine intelligence*. 2021 Oct 6;44(11):7436-56.
- [18]. Li Z, Liu F, Yang W, Peng S, Zhou J. A survey of convolutional neural networks: analysis, applications, and prospects. *IEEE transactions on neural networks and learning systems*. 2021 Jun 10;33(12):6999-7019.
- [19]. Ma S, Zhang X, Jia C, Zhao Z, Wang S, Wang S. Image and video compression with neural networks: A review. *IEEE Transactions on Circuits and Systems for Video Technology*. 2019 Apr 17;30(6):1683-98.
- [20]. Calzolari G, Liu W. Deep learning to replace, improve, or aid CFD analysis in built environment applications: A review. *Building and Environment*. 2021 Dec 1;206:108315.



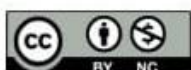


- [21]. Szandała T. Review and comparison of commonly used activation functions for deep neural networks. In *Bio-inspired neurocomputing 2020 Jul 22* (pp. 203-224). Singapore: Springer Singapore.
- [22]. Liu X, Tian S, Tao F, Yu W. A review of artificial neural networks in the constitutive modeling of composite materials. *Composites Part B: Engineering*. 2021 Nov 1;224:109152.
- [23]. Garud KS, Jayaraj S, Lee MY. A review on modeling of solar photovoltaic systems using artificial neural networks, fuzzy logic, genetic algorithm and hybrid models. *International Journal of Energy Research*. 2021 Jan;45(1):6-35.
- [24]. Kaveh A. *Applications of artificial neural networks and machine learning in civil engineering*. Cham, Switzerland: Springer; 2024 Jul 29.
- [25]. Rahman MM, Shakeri M, Tiong SK, Khatun F, Amin N, Pasupuleti J, Hasan MK. Prospective methodologies in hybrid renewable energy systems for energy prediction using artificial neural networks. *Sustainability*. 2021 Feb 23;13(4):2393.
- [26]. Ferrero Bermejo J, Gomez Fernandez JF, Olivencia Polo F, Crespo Marquez A. A review of the use of artificial neural network models for energy and reliability prediction. A study of the solar PV, hydraulic and wind energy sources. *Applied Sciences*. 2019 May 5;9(9):1844.
- [27]. Abd Elaziz M, Dahou A, Abualigah L, Yu L, Alshinwan M, Khasawneh AM, Lu S. Advanced metaheuristic optimization techniques in applications of deep neural networks: a review. *Neural Computing and Applications*. 2021 Nov;33(21):14079-99.
- [28]. Dhillon A, Verma GK. Convolutional neural network: a review of models, methodologies and applications to object detection. *Progress in Artificial Intelligence*. 2020 Jun;9(2):85-112.
- [29]. Lê MT, Wolinski P, Arbel J. Efficient neural networks for tiny machine learning: A comprehensive review. *ACM Transactions on Intelligent Systems and Technology*. 2023 Nov 20.
- [30]. Joshi G, Walambe R, Kotecha K. A review on explainability in multimodal deep neural nets. *IEEe Access*. 2021 Mar 31;9:59800-21.
- [31]. Naranjo-Torres J, Mora M, Hernández-García R, Barrientos RJ, Fredes C, Valenzuela A. A review of convolutional neural network applied to fruit image processing. *Applied Sciences*. 2020 May 16;10(10):3443.
- [32]. Khodayar M, Liu G, Wang J, Khodayar ME. Deep learning in power systems research: A review. *CSEE Journal of Power and Energy Systems*. 2020 Nov 20;7(2):209-20.



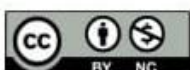


- [33]. Travassos XL, Avila SL, Ida N. Artificial neural networks and machine learning techniques applied to ground penetrating radar: A review. *Applied Computing and Informatics*. 2021 Apr 29;17(2):296-308.
- [34]. Schmidgall S, Ziaei R, Achterberg J, Kirsch L, Hajiseyedrazi S, Eshraghian J. Brain-inspired learning in artificial neural networks: A review. *APL Machine Learning*. 2024 Jun 1;2(2).
- [35]. Chen J, Liu Y. Fatigue modeling using neural networks: A comprehensive review. *Fatigue & Fracture of Engineering Materials & Structures*. 2022 Apr;45(4):945-79.
- [36]. Miller DJ, Xiang Z, Kesidis G. Adversarial learning targeting deep neural network classification: A comprehensive review of defenses against attacks. *Proceedings of the IEEE*. 2020 Feb 26;108(3):402-33.
- [37]. Bhagya Raj GV, Dash KK. Comprehensive study on applications of artificial neural network in food process modeling. *Critical reviews in food science and nutrition*. 2022 Apr 5;62(10):2756-83.
- [38]. Rajendran B, Sebastian A, Schmuker M, Srinivasa N, Eleftheriou E. Low-power neuromorphic hardware for signal processing applications: A review of architectural and system-level design approaches. *IEEE Signal Processing Magazine*. 2019 Oct 31;36(6):97-110.
- [39]. Chen Y, Song L, Liu Y, Yang L, Li D. A review of the artificial neural network models for water quality prediction. *Applied Sciences*. 2020 Aug 20;10(17):5776.
- [40]. Purwono P, Ma'arif A, Rahmaniar W, Fathurrahman HI, Frisky AZ, ul Haq QM. Understanding of convolutional neural network (cnn): A review. *International Journal of Robotics and Control Systems*. 2022;2(4):739-48.
- [41]. Escamilla-García A, Soto-Zarazúa GM, Toledano-Ayala M, Rivas-Araiza E, Gastélum-Barrios A. Applications of artificial neural networks in greenhouse technology and overview for smart agriculture development. *Applied Sciences*. 2020 May 31;10(11):3835.
- [42]. Sun K, Chen J, Yan X. The future of memristors: Materials engineering and neural networks. *Advanced Functional Materials*. 2021 Feb;31(8):2006773.
- [43]. Purwono P, Ma'arif A, Rahmaniar W, Fathurrahman HI, Frisky AZ, ul Haq QM. Understanding of convolutional neural network (cnn): A review. *International Journal of Robotics and Control Systems*. 2022;2(4):739-48.
- [44]. Tulbure AA, Tulbure AA, Dulf EH. A review on modern defect detection models using DCNNs–Deep convolutional neural networks. *Journal of Advanced Research*. 2022 Jan 1;35:33-48. Chandrasekaran R, Paramasivan SK. Advances in deep learning techniques for





- short-term energy load forecasting applications: A review. *Archives of Computational Methods in Engineering*. 2025 Mar;32(2):663-92.
- [45]. Dash T, Chitlangia S, Ahuja A, Srinivasan A. A review of some techniques for inclusion of domain-knowledge into deep neural networks. *Scientific Reports*. 2022 Jan 20;12(1):1040.
- [46]. Li G, Huang Y, Chen Z, Chesser Jr GD, Purswell JL, Linhoss J, Zhao Y. Practices and applications of convolutional neural network-based computer vision systems in animal farming: A review. *Sensors*. 2021 Feb 21;21(4):1492.
- [47]. Kabir HD, Khosravi A, Hosen MA, Nahavandi S. Neural network-based uncertainty quantification: A survey of methodologies and applications. *IEEE access*. 2018 Jun 4;6:36218-34.
- [48]. Goel A, Goel AK, Kumar A. The role of artificial neural network and machine learning in utilizing spatial information. *Spatial Information Research*. 2023 Jun;31(3):275-85.
- [49]. Zhang W, Li H, Li Y, Liu H, Chen Y, Ding X. Application of deep learning algorithms in geotechnical engineering: a short critical review. *Artificial Intelligence Review*. 2021 Dec;54(8):5633-73.
- [50]. Arbel J, Pitas K, Vladimirova M, Fortuin V. A primer on Bayesian neural networks: review and debates. *Statistical Science*. 2026 May;41(2):316-53.
- [51]. Naskath J, Sivakamasundari G, Begum AA. A study on different deep learning algorithms used in deep neural nets: MLP SOM and DBN. *Wireless personal communications*. 2022 Oct 19;128(4):2913.
- [52]. Pandey D, Niwaria K, Chourasia B. Machine learning algorithms: a review. *Mach. Learn*. 2019 Feb;6(2):916-22.
- [53]. Dike HU, Zhou Y, Deveerasetty KK, Wu Q. Unsupervised learning based on artificial neural network: A review. In 2018 IEEE International Conference on Cyborg and Bionic Systems (CBS) 2018 Oct 25 (pp. 322-327). IEEE.
- [54]. Park WJ, Park JB. History and application of artificial neural networks in dentistry. *European journal of dentistry*. 2018 Oct;12(04):594-601.
- [55]. Geetharamani GA, Pandian A. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. *Computers & Electrical Engineering*. 2019 Jun 1;76:323-38.
- [56]. Takahashi S, Sakaguchi Y, Kouno N, Takasawa K, Ishizu K, Akagi Y, Aoyama R, Teraya N, Bolatkan A, Shinkai N, Machino H. Comparison of vision transformers and convolutional neural networks in medical image analysis: a systematic review. *Journal of Medical Systems*. 2024 Sep 12;48(1):84.





- [57]. Philemon MD, Ismail Z, Dare J. A review of epidemic forecasting using artificial neural networks. *Epidemiology and Health System Journal*. 2019 Sep 25;6(3):132-43.
- [58]. Tealab A. Time series forecasting using artificial neural networks methodologies: A systematic review. *Future Computing and Informatics Journal*. 2018 Dec 1;3(2):334-40.
- [59]. Craik A, He Y, Contreras-Vidal JL. Deep learning for electroencephalogram (EEG) classification tasks: a review. *Journal of neural engineering*. 2019 Jun 1;16(3):031001.
- [60]. Rahmani S, Baghbani A, Bouguila N, Patterson Z. Graph neural networks for intelligent transportation systems: A survey. *IEEE Transactions on Intelligent Transportation Systems*. 2023 Mar 20;24(8):8846-85.
- [61]. Jiang G, He H, Yan J, Xie P. Multiscale convolutional neural networks for fault diagnosis of wind turbine gearbox. *IEEE Transactions on Industrial Electronics*. 2018 Jun 13;66(4):3196-207.
- [62]. Shlomi J, Battaglia P, Vlimant JR. Graph neural networks in particle physics. *Machine Learning: Science and Technology*. 2021 Mar 1;2(2):021001.
- [63]. Khan A, Sohail A, Zahoora U, Qureshi AS. A survey of the recent architectures of deep convolutional neural networks. *Artificial intelligence review*. 2020 Dec;53(8):5455-516.
- [64]. Habibi MR, Baghaee HR, Dragičević T, Blaabjerg F. Detection of false data injection cyber-attacks in DC microgrids based on recurrent neural networks. *IEEE Journal of Emerging and Selected Topics in Power Electronics*. 2020 Jan 20;9(5):5294-310.
- [65]. Chen L, Li S, Bai Q, Yang J, Jiang S, Miao Y. Review of image classification algorithms based on convolutional neural networks. *Remote Sensing*. 2021 Nov 21;13(22):4712.
- [66]. Mendez KM, Broadhurst DI, Reinke SN. The application of artificial neural networks in metabolomics: a historical perspective. *Metabolomics*. 2019 Nov 1;15(11):1-4.
- [67]. Jiang J, Chen M, Fan JA. Deep neural networks for the evaluation and design of photonic devices. *Nature Reviews Materials*. 2021 Aug;6(8):679-700.
- [68]. Neftci EO, Mostafa H, Zenke F. Surrogate gradient learning in spiking neural networks. *IEEE Signal Processing Magazine*. 2019 Nov;36(6):51-63.
- [69]. Salehin I, Kang DK. A review on dropout regularization approaches for deep neural networks within the scholarly domain. *Electronics*. 2023 Jul 17;12(14):3106.
- [70]. Mehonic A, Sebastian A, Rajendran B, Simeone O, Vasilaki E, Kenyon AJ. Memristors—From in-memory computing, deep learning acceleration, and spiking neural networks to the future of neuromorphic and bio-inspired computing. *Advanced Intelligent Systems*. 2020 Nov;2(11):2000085.





- [71]. Lucas A, Iliadis M, Molina R, Katsaggelos AK. Using deep neural networks for inverse problems in imaging: beyond analytical methods. *IEEE Signal Processing Magazine*. 2018 Jan 10;35(1):20-36.
- [72]. Dhall D, Kaur R, Juneja M. Machine learning: a review of the algorithms and its applications. *Proceedings of ICRIC 2019: Recent innovations in computing*. 2019 Nov 22:47-63.
- [73]. Tang J, Yuan F, Shen X, Wang Z, Rao M, He Y, Sun Y, Li X, Zhang W, Li Y, Gao B. Bridging biological and artificial neural networks with emerging neuromorphic devices: fundamentals, progress, and challenges. *Advanced materials*. 2019 Dec;31(49):1902761.
- [74]. Williamson IA, Hughes TW, Minkov M, Bartlett B, Pai S, Fan S. Reprogrammable electro-optic nonlinear activation functions for optical neural networks. *IEEE Journal of Selected Topics in Quantum Electronics*. 2019 Jul 23;26(1):1-2.
- [75]. Ghritlahre HK, Prasad RK. Application of ANN technique to predict the performance of solar collector systems-A review. *Renewable and Sustainable Energy Reviews*. 2018 Mar 1;84:75-88.
- [76]. Srinivasan PA, Guastoni L, Azizpour H, Schlatter PH, Vinuesa R. Predictions of turbulent shear flows using deep neural networks. *Physical Review Fluids*. 2019 May;4(5):054603.
- [77]. Mukhopadhyay SC, Tyagi SK, Suryadevara NK, Piuri V, Scotti F, Zeadally S. Artificial intelligence-based sensors for next generation IoT applications: A review. *IEEE Sensors Journal*. 2021 Jan 29;21(22):24920-32.
- [78]. Bing R, Yuan G, Zhu M, Meng F, Ma H, Qiao S. Heterogeneous graph neural networks analysis: a survey of techniques, evaluations and applications. *Artificial Intelligence Review*. 2023 Aug 1;56(8).
- [79]. Narkhede MV, Bartakke PP, Sutaone MS. A review on weight initialization strategies for neural networks. *Artificial intelligence review*. 2022 Jan;55(1):291-322.

