Global Trends in Science and Technology

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

Artificial Intelligence in Electrical Systems: A Review of Machine Learning Methods, Applications, and Future Perspectives

Fawad Khan[1*]

[1]Trine University, USA

[1]Fawadkhank313@gmail.com

Corresponding Author
Fawad Khan
Fawadkhank313@gmail.com

Article History:
Submitted: 04-07-2026
Accepted: 02-08-2026
Published: 07-08-2026

Keywords

Artificial Intelligence, Machine Learning, Electrical Systems, Predictive Maintenance, Renewable Energy Forecasting.

ABSTRACT

The integration of Artificial Intelligence (AI) has emerged as a crucial technology for making electrical systems intelligent and efficient.AI has been a pivotal technology in making electrical systems intelligent and efficient, enhancing automation, reliability, and decision-making. In this review, the integration of AI within the field of electrical engineering is explored, highlighting the role of machine learning techniques, deep learning models, and their applications in various areas such as smart grid, renewable energy prediction, fault detection, energy prediction, and predictive maintenance. It also covers benchmark datasets, evaluation platforms, and the performance of AI algorithms. In addition, the review identifies key challenges, such as Interpretability of the Models, Data Quality, Security of Data and Computational Complexity, and investigates new trends like Explainable AI, Digital Twins, Federated Learning and Edge AI for future electrical systems.

INTRODUCTION

One of the most revolutionary technologies that is enabling innovation across engineering disciplines is Artificial Intelligence (AI) and electrical systems are one of the areas that have benefited the most. In today's complex electrical networks, where there is increasing need for reliable, efficient, and sustainable energy solutions, AI-based methodologies are gaining momentum [1]. The old electrical systems were based on deterministic models, rule-based control strategies and manual decision making. These methods have worked well for the industry for decades, but they can be overwhelmed by the uncertainties brought about by integrating renewables, distributed generation, EVs and fleet shifts in load [2]. By leveraging AI, electrical systems can benefit from intelligent computational

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

techniques that allow them to learn from data, recognize patterns, make predictions, and make autonomous decisions, which can lead to improved performance and resilience [3].

The application of AI in the power generation, transmission, distribution and energy management sector has been significantly broadened in recent times through the development of machine learning (ML), deep learning (DL), reinforcement learning (RL), and data analytics. In the field of electrical engineering, AI has proven to be highly impactful in enhancing operational efficiency and system reliability in various applications, such as smart grids, intelligent protection systems, predictive maintenance, and forecasting renewable energy sources [4].AI has made significant contributions to operational efficiency and system reliability in electrical engineering, including in smart grids, intelligent protection systems, predictive maintenance, and renewable energy forecasting, among others [5].

With the proliferation of Internet of Things (IoT) devices, smart metering systems, and sensor networks, vast amounts of real-time data are now available to inform AI models, facilitating data-driven decision-making. The wide adoption of IoT devices, sophisticated metering systems, and sensor networks has opened a new avenue for gathering extensive and real-time data, enabling informed decisions through AI models [6]. All these advances have given rise to new electrical infrastructures that are intelligent, adaptive, and self-optimizing, responding dynamically to changing operating conditions.

Modeling complex nonlinear relationships without the need to explicitly formulate them has made machine learning a major component of AI, especially relevant in the field of electrical engineering. The algorithms have been used successfully in load forecasting, equipment health monitoring, power quality assessment, cyber-attack detection, and energy optimization [7]. The use of deep learning technologies such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks has also contributed to the advancement of accuracy in image-based inspections, time-series forecasting, and fault classification. Furthermore, new technologies like explainable AI (XAI), federated learning, edge intelligence and digital twins are tackling issues of transparency, privacy, scalability and real-time decision-making in electrical systems [8].

However, there are still several challenges that need to be addressed to make AI technologies more widely adopted in the field of electrical engineering. While these developments are promising, there are still a number of obstacles to be overcome in order for these AI technologies to become more widely used in electrical engineering [9]. The quality of the available datasets, computational needs, model explain ability, cyber security threats and integration with existing infrastructure are still major

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

challenges. Moreover, a significant number of AI models are created and tested through simulation, but need to be tested in the actual operating conditions before going to scale [10]. Robustness, reliability, and adherence to industrial standards are therefore key to ensuring trustworthy AI-enabled electrical systems.

The purpose of this review is to present an overview of the ways artificial intelligence (AI) can be applied to electrical systems, including an introduction to the basic machine learning techniques and examples of their various applications, as well as existing challenges and research directions. The article draws on insights from recent research to discuss the advantages and disadvantages of the current AI methods and opportunities for future research. In addition, it covers future trends in intelligent electrical systems like physics-informed machine learning, explainable AI, quantum machine learning, and autonomous smart grid systems that are likely to drive future intelligent electrical systems. This review provides a comprehensive overview of the latest advancements, making it an essential resource for researchers, engineers, policymakers, and practitioners involved in the field of electrical engineering and interested in the future of AI-driven solutions for resilient, efficient, and sustainable energy systems.

BASIC PRINCIPLES OF ARTIFICIAL INTELLIGENCE IN ELECTRICAL SYSTEMS

Artificial Intelligence (AI) is an interdisciplinary field devoted to the creation of computing systems that can execute tasks normally done by humans in the fields of learning, reasoning, problem solving, perception and decision making. In the realm of electrical systems, AI is playing a pivotal role in enhancing system reliability, operational efficiency, and automation [11]. AI systems can adapt based on past data, real-time data, as well as identifying complex patterns, and continuously tuning their operations based on the ever-changing nature of the system.AI can learn from the past and real-time data, recognize complex patterns, and continually adjust their operations to meet changing system requirements, unlike traditional control systems that are based on predefined mathematical models and fixed operating rules [12]. Such capability is especially important in today's electrical network, where the increased integration of renewable energy sources, distributed generation, electric vehicles and smart devices has added uncertainty and complexity to the operation of the network.

Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), Computer Vision, Natural Language Processing (NLP), optimization algorithms, and data analytics are the key pieces of technology that form the backbone of AI in electrical systems. Of these, machine learning is the most popular, as it allows computers to discover relationships in large datasets without the need for explicit coding [13]. Unsupervised learning algorithms detect hidden structures and clusters in unlabeled data (e.g., anomaly detection, customer segmentation), while supervised learning

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

algorithms predict outputs based on labeled data (e.g., electrical loads demand prediction, equipment failure prediction). Reinforcement learning also enhances the capabilities of AI, allowing intelligent agents to learn the best way to navigate a dynamic electrical environment [14].

One of the recent breakthroughs in machine learning, deep learning, is a specialized approach that relies on multi-layer neural networks to learn hierarchically from vast amounts of data and has improved the capabilities of AI systems greatly. The drone and thermal imaging systems are used extensively for image-based inspection of electrical equipment, transmission lines and substations, and architectures like Convolutional Neural Networks (CNNs) are widely used [15]. Like this, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are well suited for sequential and time-series data analysis, which is applicable in electricity demand forecasting, renewable energy prediction, and power quality monitoring.

Large-scale data created by advanced metering infrastructure, smart sensors, phasor measurement units (PMUs), supervisory control and data acquisition (SCADA) systems, and Internet of Things (IoT) devices are also a basic component of AI in electrical systems [16]. These technologies gather data on the operation of the power systems on a continuous basis, forming massive amounts of data which are the main feed-in to the AI algorithms. To enhance the accuracy of models and lower computational complexity, data preprocessing methods like cleaning, normalizing, extracting features, and reducing dimensionality are crucial [17]. AI models can learn representative patterns and make accurate predictions when operating in different conditions with high-quality data.

Optimization is also crucial in AI-powered electrical systems. A number of operational issues like economic dispatch, unit commitment, optimal power flow, voltage regulation, energy management etc. are complex optimization problems with multiple objectives and constraints. Methods like genetic algorithms, Particle Swarm Optimization, Ant Colony Optimization and Hybrid Machine Learning Models are efficient solutions for solving these nonlinear optimization problems and can outperform conventional optimization techniques in terms of convergence and adaptability [18].

The latest advancements have also brought in advanced AI paradigms, enhancing transparency, scalability, and real-time applicability. Explainable Artificial Intelligence (XAI) makes AI systems easier to understand, making the interpretation of predictions explicitly understandable and helping to boost user confidence in safety-critical electrical applications [19]. Edge AI facilitates smart devices to process data intelligently on the edge, minimizing communication latency and aiding real-time decision making in the smart grid and industrial automation. In addition, digital twin technology combines AI with virtual representation of the physical electrical equipment, enabling the ongoing monitoring, forecasting and optimization of the performance of such equipment throughout the entire

Global Trends in Science and Technology
ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

system lifecycle [20].

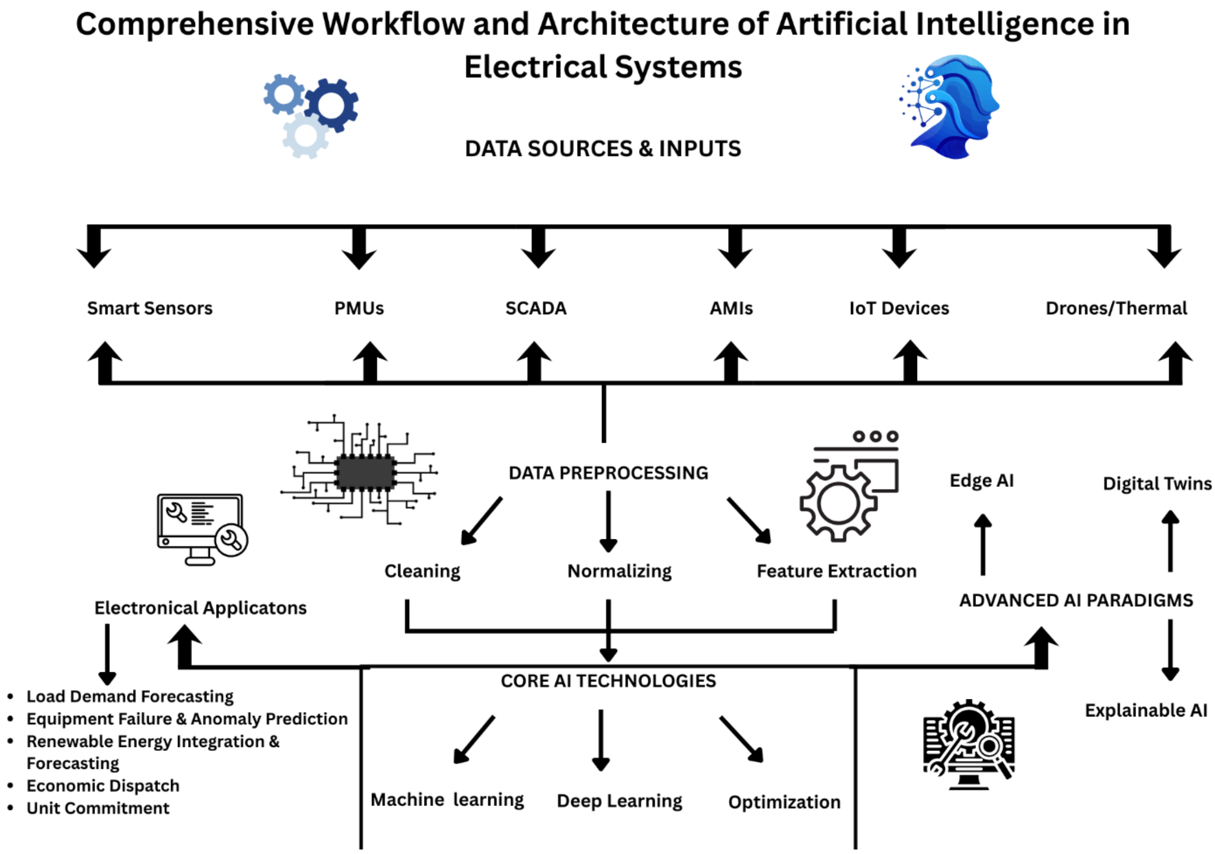

Figure 1. Integrated Framework of AI Technologies, Data Pipelines, and Applications in Modern Power Grids

MACHINE LEARNING TECHNIQUES USED IN ELECTRICAL ENGINEERING

One of the most powerful and significant fields of AI within electrical engineering is machine learning (ML), which is the power of extracting meaningful knowledge from vast amounts of data and predicting accurately without just relying on explicit mathematical models. Smart meters, phasor measurement units (PMUs), supervisory control and data acquisition (SCADA) and the Internet of Things (IoT) sensors, in addition to intelligent electronic devices generate a huge amount of data within modern electrical systems [21]. These data sources will give useful data about the behavior of the system, equipment performance, energy use, and fault conditions. These datasets are essential for machine learning techniques, which are vital in creating intelligent electrical systems by uncovering hidden patterns, categorizing operational states, predicting future events, and optimizing system performance [22].

The types of machine learning algorithms are basically divided into four categories: supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning. The most common method employed in the field of electrical engineering is supervised learning, which

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

involves training models with labeled datasets that provide input and output data [23]. These algorithms include linear regression, decision trees, random forest, support vector machines (SVM), k-nearest neighbors (KNN), and artificial neural networks (ANNs) and are all widely used in load forecasting, renewable energy prediction, transformer health assessment, fault classification and electricity price forecasting. The techniques are highly predictive when a good amount of training data is available and are now commonplace in many operational and planning applications [24].

Unsupervised Learning Methods: These methods make use of unlabeled data sets for the purposes of identifying hidden structures, clusters or abnormalities, with no known output label. They are commonly used algorithms such as K-means clustering, hierarchical clustering, principal component analysis (PCA), self-organizing maps (SOM), and Gaussian mixture models [25]. These techniques are widely used in electrical engineering for customer load profiling, anomaly detection in smart grid, power quality assessment, feature extraction and condition monitoring of electrical equipment. Unsupervised learning helps to optimize system planning and operational choices by detecting unexpected operating conditions and clustering consumers according to their energy consumption patterns [26].

A specialized form of machine learning, deep learning, has made a huge stride in the ability of intelligent electric systems. Deep neural networks are based on a series of hidden layers, allowing them to automatically learn hierarchical features from big and complex data sets. The Convolutional Neural Networks (CNNs) are very useful in image recognition tasks like transmission line, substation, solar panel and electrical equipment defect detection from thermal images or visual images [27]. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are used to analyse sequential data with wide application in load demand forecasting, renewable energy generation prediction, battery state estimation and power system stability analysis [28]. Recently, transformer architectures have shown to be superior in long-term time-series prediction and energy management tasks.

Reinforcement learning is another type of important machine learning paradigm that involves an intelligent agent learning the best possible control strategy through interaction with the environment and receiving reward and/or penalty signals depending on the actions taken by the agent. In contrast to supervised learning, reinforcement learning does not need labeled data sets and it is well suited to dynamic optimization problems [29]. It can be used for smart grid energy management, voltage control, demand response, coordination of charging electric vehicles, and autonomous operation of microgrids. Deep reinforcement learning also improves these capabilities by integrating reinforcement learning with deep neural networks, which makes it possible to make effective

Global Trends in Science and Technology
ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

decisions in complex and high-dimensional electrical systems [30].

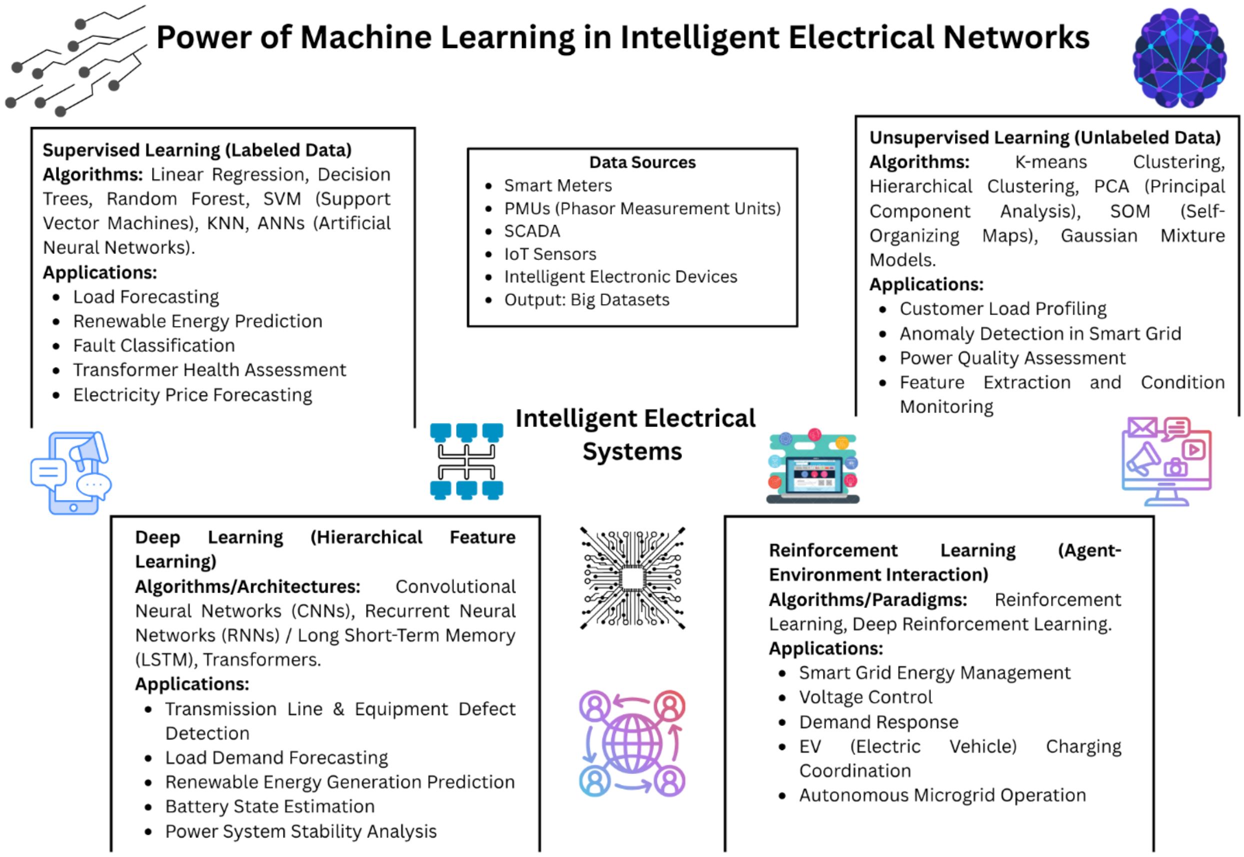

Figure 2. Machine Learning Applications in Modern Electrical Systems

AI APPLICATIONS IN ELECTRICAL SYSTEMS

Artificial Intelligence (AI) is revolutionizing modern electrical systems by empowering them to monitor, automate, optimize, and make decisions intelligently throughout the electricity value chain. The complexity of electrical networks has dramatically grown due to the proliferation of renewable energy resources, distributed energy resources, electric vehicles, smart grids and advanced communication technologies [31]. There is difficulty in effectively managing these dynamic and uncertain environments using conventional analytical and rule-based approaches. AI can overcome these challenges by leveraging machine learning, deep learning, reinforcement learning, and optimization algorithms to process vast amounts of operation data, forecast future system performance and facilitate autonomous control [32]. As a result, AI has become an integral part of enhancing the efficiency, reliability, security, and sustainability of modern electrical systems.

AI has the potential to transform the energy sector, particularly in smart grid management, where intelligent algorithms can optimize electricity generation, transmission, distribution, and consumption processes. AI can help in real-time monitoring of grid conditions, forecasting of demand, voltage

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

management, and managing congestion, while also enabling the seamless integration of renewable energy sources [33]. AI models can identify abnormal operating conditions by analyzing the data gathered from smart meters, sensors, and Supervisory Control and Data Acquisition (SCADA) systems and suggest corrective measures before system failures occur. The features help mitigate risk to the grid and lower operational expenses and energy use [34].

AI also has a crucial role to play in load forecasting and renewable energy forecasting. Forecasting of the future electricity demand is crucial for the economic dispatch, generation scheduling and power system stability. The machine learning models have shown to perform better than the traditional statistical models in terms of forecasting accuracy, such as the models based on Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Long Short-Term Memory (LSTM) networks, and transformer-based architectures [35]. Likewise, AI is applied in a vast number of ways to forecast solar irradiance and wind speed to improve the effective integration of renewable energy into power systems and mitigate the volatility of renewable energy sources.

One of the other applications is fault detection, diagnosis and predictive maintenance. Operational data is generated continuously from embedded sensors and monitoring devices in electrical equipment such as transformers, generators, circuit breakers, motors and transmission lines [36]. These data are used to detect early signs of equipment degradation, equipment insulation failure, overheating and abnormal vibrations with the help of AI algorithms. AI-driven predictive maintenance ensures equipment performance, reduces maintenance expenses, and extends equipment life by proactively planning maintenance tasks before equipment failure [37].

AI also contributes to the identification and classification of disturbances like voltage sags, swells, harmonics, transients, and frequency deviations in power quality monitoring and protection systems. Advanced technologies such as deep learning and signal processing allow the fast detection of faults and to operate intelligent protective relays that isolate faulted sections to a high degree of accuracy [38]. These smart protection systems help to reduce recovery times and resilience of electrical networks.

AI is also now essential in energy management systems, microgrids and electric vehicle (EV) infrastructure. Smart energy management algorithms can be used to improve the efficiency of energy generation, storage, and use, by optimizing the power generation, storage, and consumption to meet the demands of the end-users [39]. AI plays a vital role in microgrids by enabling them to operate independently, schedule energy usage optimally, and transition seamlessly between grid-connected and off-grid conditions. For EV charging networks, AI optimizes charging schedules, predicts charging demand, manages battery health and minimizes the effect of large-scale EV integration on

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

the distribution network [40].

AI ALGORITHMS AND COMPARATIVE PERFORMANCE

AI algorithms are essential in today's electrical systems for their ability to handle large volumes of complex data, detect patterns and trends that would not be apparent to humans, and enable intelligent decision-making. The performance of the various algorithms varies according to the type of electrical engineering problem, the amount and quality of training data available, computational needs, and operational needs [41]. Therefore, the choice of the best possible algorithm is crucial for the prediction to be accurate, optimization to be efficient, and system performance to be reliable. AI algorithms can be compared with one another and used to gain insight into their performance in various applications like load forecasting, fault diagnosis, renewable energy prediction, predictive maintenance, power quality assessment and smart grid management [42].

Despite these developments, traditional machine learning models such as Linear Regression, Decision Trees, Support Vector Machines (SVM), Random Forests and Artificial Neural Networks (ANNs) are still widely used for their simplicity and interpretability, which is particularly important for data-driven decision making [43]. Linear Regression is applicable to simple forecast problems, where the relationship is linear, and it is not effective in forecasting problems where the behavior of the electrical system is highly nonlinear. Decision Trees provide clear decision making capabilities and can be easily understood, but can over fit complex data sets. Random Forests combat these difficulties by using multiple decision trees, enhance prediction accuracy, increase robustness and lower variance [44]. Likewise, SVM has been shown to perform well in fault classification, power quality analysis and equipment condition monitoring in cases of small training datasets.

In certain problems involving large-scale and high-dimensional datasets, deep learning algorithms have substantially improved the performance of a myriad of traditional machine learning methods. Convolutional Neural Networks (CNNs) have been found to be accurate in image-based inspection tasks such as defect detection, using thermal and visual images, of transmission lines, substations, transformers and photovoltaic panels [45]. For sequential data analysis, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are tailored specifically for them, and are currently the most commonly used algorithms for electricity demand forecasting, renewable energy prediction, battery health estimation, and dynamic stability assessment [46]. Transformer-based neural networks are more recently found to have an immense potential in long-term time-series forecasting tasks by successfully capturing complex temporal relationships, which in some cases outperform classical recurrent architectures.

Another category of AI algorithms that are well-suited for optimization and autonomous control

Global Trends in Science and Technology
ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

problem is called Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL). Unlike supervised learning methods which depend on labeled datasets, reinforcement learning helps intelligent agents learn optimal control strategies in dynamic environment by interacting with these environments [47]. RL is used in the electrical engineering field to voltage regulation, energy management, demand response, electric vehicle charging coordination, and operation of the micro grid. The Deep Reinforcement Learning brings these abilities together by incorporating deep neural networks, enabling intelligent decision-making in highly complex and ever-evolving electrical systems [48].

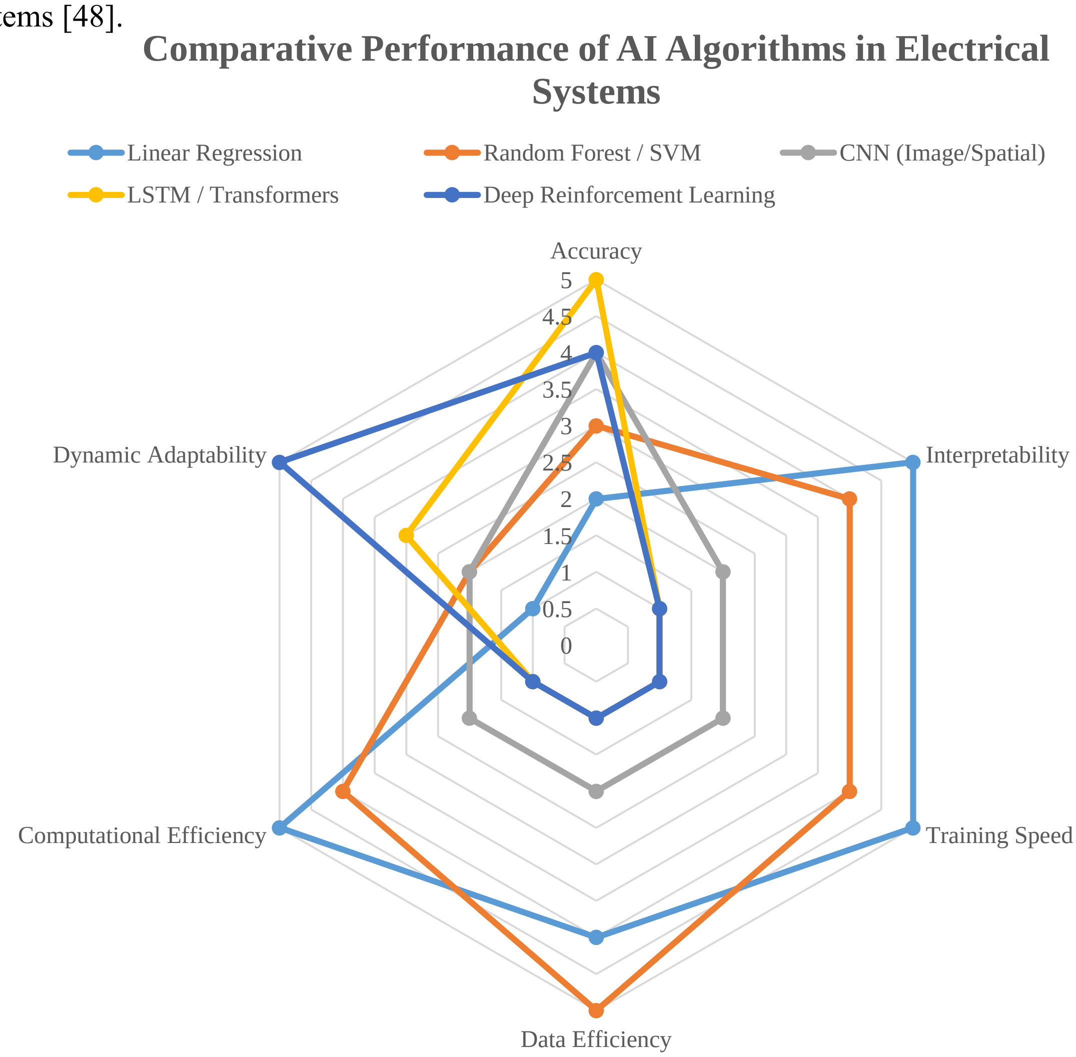

Figure 3. Comparative Performance of AI Algorithms in Electrical Systems

The effectiveness of the AI algorithms are normally assessed by quantitative measures like accuracy, precision, recall, F1-score, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), computational time, convergence speed, and memory use. The deep learning-based models typically have higher prediction accuracy but are more costly in terms of computation power, large labeled data and training time [49]. However, traditional machine learning

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

algorithms tend to be faster to train, require less computation, and are more interpretable, which can be useful in scenarios with fewer data points or real-time constraints. While reinforcement learning offers unparalleled adaptability in dynamic environments, it can be time-consuming and must be trained with careful design of the reward function for stable convergence [50].

DATASETS AND BENCHMARK PLATFORMS

Quality, diversity, and availability of datasets play a pivotal role in the effectiveness of AI models for electrical systems. These high quality datasets can be used to train machine learning systems to learn system behavior, identify operating patterns, identify anomalies, and make reliable predictions within different operating conditions [51]. The amount of operational information has increased significantly as electrical systems are becoming increasingly digitized through smart grids, the Internet of Things (IoT), advanced metering infrastructure (AMI), Supervisory Control and Data Acquisition (SCADA) and Phasor Measurement Units (PMUs) [52]. These data are valuable in understanding power generation, transmission, distribution, equipment status, energy usage, renewable energy generation, and occurrences of faults and much more, enabling the creation of intelligent AI-based applications.

Benchmark datasets are essential for driving forward the AI research field because they enable researchers to test and compare algorithms to a common standard. Popular datasets are electricity load profiles, PV power generation data, wind speed data, wind power data, smart meter data, battery performance data, and transformer condition monitoring data, power quality disturbance data and databases [53]. Besides, other organizations like IEEE Power & Energy Society, National Renewable Energy Laboratory (NREL), UCI Machine Learning Repository, Kaggle, and Open Power System Data have datasets commonly used in forecasting, classification, optimization and fault diagnosis studies. These benchmark datasets pave the way for reproducible research, provide a valid basis for comparing the performance of AI models, and stimulate innovation in the entire electrical engineering community [54].

However, it is difficult to find publicly available datasets that can be used to capture the variety of operating conditions commonly found in real-world electrical networks in most practical applications. As a result, researchers frequently gather private data from either field measurements, experiments in the laboratory, industrial monitoring systems, or utility databases [55]. The data may contain voltage, current, frequency, temperature, vibration, dissolved gas analysis, thermal images, weather and equipment operating parameters. Raw data is normally processed using data cleansing, normalization, and handling missing data, feature extraction, feature selection, and dimensionality reduction before it is employed in the development of the AI model [56]. These techniques have a number of benefits and are well suited to the data that is used for machine learning.The aim of these preprocessing

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

techniques is to enhance the quality of the data, reduce computational complexity, and boost the performance of the machine learning algorithms used for the predictions [57].

In addition to benchmark platforms, simulation platforms are also crucial for AI research, as they offer a controlled environment for testing algorithms across various operating scenarios. MATLAB/Simulink, PSCAD, Dig SILENT Power Factory, PSSE, OpenDSS, GridLAB-D and ETAP are power system simulation software that can be used to create realistic datasets for power flow analysis, transient stability studies, renewable energy integration, fault simulation and micro grid operation [58]. These simulation platforms can be especially useful where there is a lack of real data, it is confidential, or it may not be easily acquired. Moreover, digital twin technology has become an advanced benchmarking tool, which involves simulating physical electrical systems in the virtual world and continually updating them with operational data, facilitating predictive maintenance, system optimization and intelligent monitoring [59].

AI model performance is measured by the same standard metrics to enable cross-study comparison. Examples of common evaluation measures are accuracy, precision, recall, F1-score, mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), coefficient of determination (R^2), computational time, and model robustness. These metrics enable a researcher to determine the success of a prediction, classification performance, computational efficiency and generalization performance at varying operating conditions [60].

OBSTACLES TO AI-BASED ELECTRICAL SYSTEMS

AI has transformed how electrical systems are monitored, analyzed, and managed, with intelligent systems monitoring, forecasting, and making decisions autonomously, thereby enhancing energy efficiency and management in power generation, transmission, and distribution. Yet, many technical, operational, economic, and regulatory hurdles stand in the way of the broad-scale use of AI in real-world electrical engineering tasks [61]. In conclusion, tackling these challenges is crucial for realizing the potential of AI in electrical systems, making them more reliable, secure, transparent, and efficient to meet the growing demands of modern energy infrastructures.

Data availability and quality is one of the main obstacles. AI algorithms need extensive and well-structured data to be effective at training and predicting. But, in electrical utility applications there are many problems like missing data, noisy measurements, different data formats and fewer historical data [62]. In addition, operational data are often gathered from a variety of sensors, smart meters, SCADA systems and Internet of Things (IoT) devices that utilize different communication protocols. Low-quality data can lead to inaccurate models, high error rates in predictions, and restrict the model's applicability to AI algorithms. To ensure the reliability of AI models, effective data preprocessing,

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

feature engineering, and data validation are required [63].

Computational complexity and scalability are also a major hurdle. These advanced deep learning models, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and transformer architectures, can be computationally intensive, have high memory needs, and necessitate specialized hardware like Graphics Processing Units (GPUs) [64]. This adds implementation costs and can make this a challenging technology to deploy in real time in resource-limited environments, such as a remote substation or edge device. Creating lightweight and low computation AI models is an ongoing research topic [65].

Interpretability and explain ability of the model also are critical concerns. There are many AI models that are very effective and are known as the "black boxes" because the engineers or system operators don't know how the predictions or decisions are made. For safety-critical applications like fault protection, grid stability assessment, and equipment health monitoring in electrical power systems, clear decision-making is vital to build user confidence and ensure regulatory compliance [66]. Explainable Artificial Intelligence (XAI) has come up as a potential solution to explain the decisions made by the AI or bring about interpretable explanations for the AI predictions, but reaching the optimum level of balance between model accuracy and explain ability is still a significant challenge [67].

Security and data privacy are other challenges to AI implementation. Modern electrical systems heavily depend on the communication networks, cloud systems and devices connected to the Internet of Things (IoT), all of which are susceptible to cyber-attacks, data breaches, false data injection attacks and adversarial machine learning methods [68]. Faulty AI models could lead to wrong decisions, which could negatively impact power system safety and reliability. As a result, strong cyber security regulations, secure communication protocols, encryption techniques, and privacy preserving machine learning techniques, like federated learning, are becoming a critical aspect of the protection of AI enabled electrical infrastructures [69].

One of the other hurdles is the interoperability of AI with the old legacy systems. Older equipment and legacy control systems, that weren't designed for today's AI technologies, are still in use by many electrical utilities. The implementation of intelligent algorithms in such legacy systems can be a significant challenge and involve major upgrades, compatibility testing, and investments in digital communication infrastructure [70]. Moreover, the lack of a common coding and interoperability structure increases the complexity of the deployment of AI on a large scale in various utility networks and equipment manufacturers.

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

EMERGING TRENDS AND FUTURE PERSPECTIVES

Artificial Intelligence (AI) is still driving the transformation of contemporary electrical systems with new technologies that improve automation, intelligence, efficiency and sustainability. Given the growing data-driven and decentralized nature of power systems, new artificial intelligence tools and techniques are poised to overcome numerous challenges of traditional analytical tools [71]. The future electrical network will be based on advanced computational intelligence algorithms which will require processing huge amounts of real-time data, adjusting to changing operating conditions and assisting with autonomous decision-making [72]. These advances are likely to be significant in delivering reliable, resilient and environmentally sustainable energy systems and support global efforts toward a digital transition and carbon neutrality.

The use of Explainable Artificial Intelligence (XAI) is one of the more notable trends that is well on the horizon. While deep learning models have shown great predictive accuracy, they are less accepted in safety-critical electrical applications due to their lack of transparency [73]. XAI aims to rectify this by generating understandable explanations for model decisions, helping engineers and system operators to understand the rationale behind automated decisions. Gaining better explain ability is hoped to boost trust, streamline regulatory requirements and help to expand the use of AI-based electrical technologies across industry [74].

Edge Artificial Intelligence is another interesting path to follow, as it allows for data processing to occur at local devices and not just the central cloud. Smart sensors, intelligent electronic devices, substations, and Internet of Things (IoT) nodes with edge AI can, with minimal communication delay, monitor, detect anomalies, and diagnose faults in real time [75]. This feature is especially advantageous for applications that demand quick reaction times, including protection systems, microgrid control, and industrial automation. Edge AI also helps to save bandwidth and improve data privacy by limiting the sharing of sensitive operational data [76].

It is believed that Digital Twin technology will be an integral part of the future intelligent electrical systems. A digital twin is a virtual asset or network of physical electrical assets that is continually updated with real-world operational data. AI combined with digital twins allows utilities to schedule maintenance and optimize maintenance without impacting the system, simulate operating scenarios, evaluate system performance and undertake predictive maintenance [77]. This technology can make a huge difference in asset management and lessen maintenance costs and unexpected equipment failures.

Another key trend for AI-powered electrical systems is the growing popularity of Federated Learning. Federated learning enables decentralized data collection and multiple organizations or devices to

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

work together to train AI models without sharing the data among them. The decentralized learning method also improves privacy, improves cybersecurity, and enables the sharing of data between each other without sharing any sensitive data on operations [78].

In addition, emerging research is also examining the integration of data-driven learning with well-known physical principles governing electrical systems, known as Physics-Informed Machine Learning (PIML). The introduction of engineering knowledge into the AI models via PIML boosts the accuracy of predictions, increases model reliability, and decreases reliance on extensive training datasets [79]. The same way, Quantum Machine Learning (QML) is also becoming popular as a potential paradigm in the future that can solve very complex optimization and power system planning problems more efficiently than classical computing approaches, but it is still an early stage of implementation [80].

CONCLUSION

Artificial Intelligence (AI) has become a game-changer in the world of modern electrical systems, revolutionizing the landscape of power generation, transmission and distribution technologies, and energy management. The application of artificial intelligence (AI) technologies, such as machine learning, deep learning, and reinforcement learning, has led to the development of more intelligent, adaptive, and efficient electrical systems. AI based methods can operate without requiring a mathematical model, or manual decision making, and use large-scale data to recognize complex patterns, forecast future system behavior, and make autonomous decisions about operation. AI is likely to become even more instrumental in tackling the challenges posed by modern electrical infrastructures as the global energy sector moves towards becoming a digitalized, decarbonized, and decentralized sector.

In this review, the basics of Artificial Intelligence has been introduced and the various kinds of machine learning algorithms have been discussed which are used in the electrical engineering field. Algorithms such as supervised learning, unsupervised learning, deep learning, and reinforcement learning have shown to have a great ability to solve complex problems in engineering fields like load forecasting, renewable energy prediction, fault diagnosis, predictive maintenance, equipment condition monitoring, power quality analysis, smart grid optimization, and energy management. These techniques have been consistently superior in predictive accuracy, operational efficiencies, system reliability and maintenance planning than many other traditional computational methods.

The review has also highlighted the need for high-quality datasets, benchmark platforms and simulation environments for the successful development and testing of AI models. Effective machine learning applications depend on reliable data that are gathered with smart sensor, advanced metering

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

infrastructure, SCADA, Internet of Things (IoT) devices and Phasor Measurement Units (PMUs). Similarly, simulation tools and digital twin technologies allow researchers to test algorithms in a variety of operating conditions, prior to their implementation in an electrical network in the field. While these metrics and benchmarks are crucial for fair comparisons, they are not universally accepted, meaning that scientists might choose to employ different ones depending on their specific research scope and audience.Although these metrics and benchmarks are very important to ensure fair comparisons between AI models, they are not agreed upon by all scientists and particular ones may be used based on the research context and audience.

While the potential benefits of AI in Electrical systems are many, there are also several key challenges to consider. However, challenges such as data quality, computational complexity, lack of interpretability, cybersecurity, privacy considerations, integration with legacy systems, and the absence of standardized implementation frameworks persist, hindering widespread use in industry. Multidisciplinary cooperation between electrical engineers, data scientists, policymakers, and industry actors is required to tackle these problems. Creating explainable, secure, efficient and credible AI models will be critical for reliable operation in safety-critical electrical applications.

REFERENCES

[1]. Cheng L, Yu T. A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems. International Journal of Energy Research. 2019 May;43(6):1928-73.

[2]. Alhamrouni I, Abdul Kahar NH, Salem M, Swadi M, Zahroui Y, Kadhim DJ, Mohamed FA, Alhuyi Nazari M. A comprehensive review on the role of artificial intelligence in power system stability, control, and protection: Insights and future directions. Applied Sciences. 2024 Jul 17;14(14):6214.

[3]. Khan MI, Ahmad B, Shoaib M, Anwar S, Ali Z. Artificial intelligence and machine learning applications in smart infrastructure and electrical systems. The Critical Review of Social Sciences Studies. 2025 Feb 21;3(1):2005-16.

[4]. Nguyen MV, Kittur J. Harnessing Artificial Intelligence for Advancements in Electrical Engineering: A Systematic Literature Review of Applications, Challenges, and Future Trends. Computer Applications in Engineering Education. 2025 Nov;33(6):e70083.

[5]. Entezari A, Aslani A, Zahedi R, Noorollahi Y. Artificial intelligence and machine learning in energy systems: A bibliographic perspective. Energy Strategy Reviews. 2023 Jan 1;45:101017.

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

[6]. Ukoba K, Olatunji KO, Adeoye E, Jen TC, Madyira DM. Optimizing renewable energy systems through artificial intelligence: Review and future prospects. Energy & environment. 2024 Nov;35(7):3833-79.

[7]. Baloch SK, Abbas T, Hussain S, Ahmed S. The Impact of Artificial Intelligence on Electrical Engineering: A Review of Current Applications and Future Prospects.

[8]. Bharaneedharan B, Panchanathan S, Kit CC, Venkatesan EP, Hasan N. Machine learning and artificial intelligence techniques for intelligent control and forecasting in energy storage-based power systems. Energy Science & Engineering. 2026 Apr;14(4):2318-44.

[9]. Strielkowski W, Vlasov A, Selivanov K, Muraviev K, Shakhnov V. Prospects and challenges of the machine learning and data-driven methods for the predictive analysis of power systems: A review. Energies. 2023 May 11;16(10):4025.

[10]. Mahmood MR, Matin MA, Sarigiannidis P, Goudos SK. A comprehensive review on artificial intelligence/machine learning algorithms for empowering the future IoT toward 6G era. IEEE access. 2022 Aug 18;10:87535-62.

[11]. Kiasari M, Ghaffari M, Aly HH. A comprehensive review of the current status of smart grid technologies for renewable energies integration and future trends: The role of machine learning and energy storage systems. Energies. 2024 Aug 19;17(16):4128.

[12]. Forootan MM, Larki I, Zahedi R, Ahmadi A. Machine learning and deep learning in energy systems: A review. Sustainability. 2022 Apr 18;14(8):4832.

[13]. Joshi A, Capezza S, Alhaji A, Chow MY. Survey on AI and machine learning techniques for microgrid energy management systems. IEEE/CAA Journal of Automatica Sinica. 2023 Jun 15;10(7):1513-29.

[14]. Nwokorie TO, Abah MA, Oladosu MA, Agida OD, Obukeajeta OD, Asogwa CO. Artificial Intelligence and Machine Learning in Electrical Power Systems: A Review of Applications and Future Directions.

[15]. Marković M, Bossart M, Hodge BM. Machine learning for modern power distribution systems: Progress and perspectives. Journal of Renewable and Sustainable Energy. 2023 May 1;15(3):032301.

[16]. Taghvaie A, Warnakulasuriya T, Kumar D, Zare F, Sharma R, Vilathgamuwa DM. A comprehensive review of harmonic issues and estimation techniques in power system networks based on traditional and artificial intelligence/machine learning. Ieee Access. 2023 Mar 22;11:31417-42.

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

[17]. Massaoudi M, Abu-Rub H, Refaat SS, Chihi I, Oueslati FS. Deep learning in smart grid technology: A review of recent advancements and future prospects. IEEE access. 2021 Apr 5;9:54558-78.

[18]. Afridi YS, Ahmad K, Hassan L. Artificial intelligence based prognostic maintenance of renewable energy systems: A review of techniques, challenges, and future research directions. International Journal of Energy Research. 2022 Dec;46(15):21619-42.

[19]. Zhang D, Han X, Deng C. Review on the research and practice of deep learning and reinforcement learning in smart grids. CSEE Journal of Power and Energy Systems. 2018 Sep 23;4(3):362-70.

[20]. Cioffi R, Travaglioni M, Piscitelli G, Petrillo A, De Felice F. Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions. Sustainability. 2020 Jan 8;12(2):492.

[21]. Helm JM, Swiergosz AM, Haeberle HS, Karnuta JM, Schaffer JL, Krebs VE, Spitzer AI, Ramkumar PN. Machine learning and artificial intelligence: definitions, applications, and future directions. Current reviews in musculoskeletal medicine. 2020 Feb;13(1):69-76.

[22]. Alimi OA, Ouahada K, Abu-Mahfouz AM. A review of machine learning approaches to power system security and stability. IEEE access. 2020 Jun 19;8:113512-31.

[23]. Benti NE, Chaka MD, Semie AG. Forecasting renewable energy generation with machine learning and deep learning: Current advances and future prospects. Sustainability. 2023 Apr 23;15(9):7087.

[24]. 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.

[25]. Mazhar T, Irfan HM, Haq I, Ullah I, Ashraf M, Shloul TA, Ghadi YY, Imran, Elkamchouchi DH. Analysis of challenges and solutions of IoT in smart grids using AI and machine learning techniques: A review. Electronics. 2023 Jan 3;12(1):242.

[26]. Deng L. Artificial intelligence in the rising wave of deep learning: The historical path and future outlook [perspectives]. IEEE Signal Processing Magazine. 2018 Jan 10;35(1):180-77.

[27]. Fahim YA, Hasani IW, Kabba S, Ragab WM. Artificial intelligence in healthcare and medicine: clinical applications, therapeutic advances, and future perspectives. European journal of medical research. 2025 Sep 23;30(1):848.

[28]. Geras KJ, Mann RM, Moy L. Artificial intelligence for mammography and digital breast tomosynthesis: current concepts and future perspectives. Radiology. 2019 Nov;293(2):246-59.

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

[29]. Lee HS, Lee J. Applying artificial intelligence in physical education and future perspectives. Sustainability. 2021 Jan 2;13(1):351.

[30]. Ali SS, Choi BJ. State-of-the-art artificial intelligence techniques for distributed smart grids: A review. Electronics. 2020 Jun 22;9(6):1030.

[31]. Araujo SO, Peres RS, Ramalho JC, Lidon F, Barata J. Machine learning applications in agriculture: current trends, challenges, and future perspectives. Agronomy. 2023 Dec 1;13(12):2976.

[32]. Goksel N, Bozkurt A. Artificial intelligence in education: Current insights and future perspectives. InHandbook of Research on Learning in the Age of Transhumanism 2019 (pp. 224-236). IGI Global.

[33]. Cao D, Hu W, Zhao J, Zhang G, Zhang B, Liu Z, Chen Z, Blaabjerg F. Reinforcement learning and its applications in modern power and energy systems: A review. Journal of modern power systems and clean energy. 2020 Nov;8(6):1029-42.

[34]. Rane NL, Paramesha M, Choudhary SP, Rane J. Artificial intelligence, machine learning, and deep learning for advanced business strategies: a review. Partners Universal International Innovation Journal. 2024 Jun 25;2(3):147-71.

[35]. Padhiary M, Saha D, Kumar R, Sethi LN, Kumar A. Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. Smart Agricultural Technology. 2024 Aug 1;8:100483.

[36]. De-Lima-Santos MF, Ceron W. Artificial intelligence in news media: Current perceptions and future outlook. Journalism and media. 2021 Dec 30;3(1):13-26.

[37]. Mak KK, Pichika MR. Artificial intelligence in drug development: present status and future prospects. Drug discovery today. 2019 Mar 1;24(3):773-80.

[38]. Tran TT, Surya Wibowo A, Tayara H, Chong KT. Artificial intelligence in drug toxicity prediction: recent advances, challenges, and future perspectives. Journal of chemical information and modeling. 2023 Apr 26;63(9):2628-43.

[39]. Arinez JF, Chang Q, Gao RX, Xu C, Zhang J. Artificial intelligence in advanced manufacturing: Current status and future outlook. Journal of Manufacturing Science and Engineering. 2020 Nov 1;142(11):110804.

[40]. Xu J, Yang P, Xue S, Sharma B, Sanchez-Martin M, Wang F, Beaty KA, Dehan E, Parikh B. Translating cancer genomics into precision medicine with artificial intelligence: applications, challenges and future perspectives. Human genetics. 2019 Feb 8;138(2):109-24.

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

[41]. Ejjami R. Enhancing cybersecurity through artificial intelligence: techniques, applications, and future perspectives. Journal of Next-Generation Research 5.0. 2024 Nov 16.

[42]. Alshawwa SZ, Kassem AA, Farid RM, Mostafa SK, Labib GS. Nanocarrier drug delivery systems: characterization, limitations, future perspectives and implementation of artificial intelligence. Pharmaceutics. 2022 Apr 18;14(4):883.

[43]. Sarker IH. Machine learning for intelligent data analysis and automation in cybersecurity: current and future prospects. Annals of Data Science. 2023 Dec;10(6):1473-98.

[44]. Chhetri KB. Applications of artificial intelligence and machine learning in food quality control and safety assessment. Food Engineering Reviews. 2024 Mar;16(1):1-21.

[45]. Lu Y. Artificial intelligence: a survey on evolution, models, applications and future trends. Journal of management analytics. 2019 Jan 2;6(1):1-29.

[46]. Kim DH, Kim TJ, Wang X, Kim M, Quan YJ, Oh JW, Min SH, Kim H, Bhandari B, Yang I, Ahn SH. Smart machining process using machine learning: A review and perspective on machining industry. International Journal of Precision Engineering and Manufacturing-Green Technology. 2018 Aug;5(4):555-68.

[47]. Dimitriadou E, Lanitis A. A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. Smart Learning Environments. 2023 Feb 6;10(1):12.

[48]. Choy G, Khalilzadeh O, Michalski M, Do S, Samir AE, Pianykh OS, Geis JR, Pandharipande PV, Brink JA, Dreyer KJ. Current applications and future impact of machine learning in radiology. Radiology. 2018 Aug;288(2):318-28.

[49]. Bourechak A, Zedadra O, Kouahla MN, Guerrieri A, Seridi H, Fortino G. At the confluence of artificial intelligence and edge computing in iot-based applications: A review and new perspectives. Sensors. 2023 Feb 2;23(3):1639.

[50]. Hunde BR, Woldeyohannes AD. Future prospects of computer-aided design (CAD)–A review from the perspective of artificial intelligence (AI), extended reality, and 3D printing. Results in Engineering. 2022 Jun 1;14:100478.

[51]. Dimiduk DM, Holm EA, Niezgoda SR. Perspectives on the impact of machine learning, deep learning, and artificial intelligence on materials, processes, and structures engineering. Integrating Materials and Manufacturing Innovation. 2018 Sep;7(3):157-72.

[52]. Hua H, Li Y, Wang T, Dong N, Li W, Cao J. Edge computing with artificial intelligence: A machine learning perspective. ACM Computing Surveys. 2023 Jan 13;55(9):1-35.

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

[53]. Olawade DB, Wada OZ, Odetayo A, David-Olawade AC, Asaolu F, Eberhardt J. Enhancing mental health with Artificial Intelligence: Current trends and future prospects. Journal of medicine, surgery, and public health. 2024 Aug 1;3:100099.

[54]. Samala AD, Rawas S, Wang T, Reed JM, Kim J, Howard NJ, Ertz M. Unveiling the landscape of generative artificial intelligence in education: a comprehensive taxonomy of applications, challenges, and future prospects. Education and Information Technologies. 2025 Feb;30(3):3239-78.

[55]. Colavizza G, Blanke T, Jeurgens C, Noordegraaf J. Archives and AI: An overview of current debates and future perspectives. ACM Journal on Computing and Cultural Heritage (JOCCH). 2021 Dec 14;15(1):1-5.

[56]. Shah P, Kendall F, Khozin S, Goosen R, Hu J, Laramie J, Ringel M, Schork N. Artificial intelligence and machine learning in clinical development: a translational perspective. NPJ digital medicine. 2019 Jul 26;2(1):69.

[57]. Du W, Ding S. A survey on multi-agent deep reinforcement learning: from the perspective of challenges and applications: Wei Du and Shifei Ding. Artificial Intelligence Review. 2021 Jun;54(5):3215-38.

[58]. Chataut R, Phoummalayvane A, Akl R. Unleashing the power of IoT: A comprehensive review of IoT applications and future prospects in healthcare, agriculture, smart homes, smart cities, and industry 4.0. Sensors. 2023 Aug 16;23(16):7194.

[59]. Himeur Y, Elnour M, Fadli F, Meskin N, Petri I, Rezgui Y, Bensaali F, Amira A. AI-big data analytics for building automation and management systems: a survey, actual challenges and future perspectives: Y. Himeur et al. Artificial intelligence review. 2023 Jun;56(6):4929-5021.

[60]. Ali Z, Saad S, Rasheed K, Ammad S. AI future perspectives and trends in construction. AI in material science. 2024 Jul 26:239-61.

[61]. 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.

[62]. Sun T, Feng B, Huo J, Xiao Y, Wang W, Peng J, Li Z, Du C, Wang W, Zou G, Liu L. Artificial intelligence meets flexible sensors: emerging smart flexible sensing systems driven by machine learning and artificial synapses. Nano-Micro Letters. 2024 Dec;16(1):14.

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

[63]. Kumar P, Hati AS. Review on Machine Learning Algorithm Based Fault Detection in Induction Motors: P. Shankar, A. Kumar. Archives of Computational Methods in Engineering. 2021 May;28(3):1929-40.

[64]. Jafar A, Bibi N, Naqvi RA, Sadeghi-Niaraki A, Jeong D. Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. Frontiers in Plant Science. 2024 Mar 13;15:1356260.

[65]. Akkus Z, Cai J, Boonrod A, Zeinoddini A, Weston AD, Philbrick KA, Erickson BJ. A survey of deep-learning applications in ultrasound: Artificial intelligence–powered ultrasound for improving clinical workflow. Journal of the American College of Radiology. 2019 Sep 1;16(9):1318-28.

[66]. Kumar M, Kumar A, Verma S, Bhattacharya P, Ghimire D, Kim SH, Hosen AS. Healthcare Internet of Things (H-IoT): Current trends, future prospects, applications, challenges, and security issues. Electronics. 2023 Apr 28;12(9):2050.

[67]. Zheng P, Wang H, Sang Z, Zhong RY, Liu Y, Liu C, Mubarok K, Yu S, Xu X. Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives. Frontiers of Mechanical Engineering. 2018 Jun;13(2):137-50.

[68]. Shafique K, Khawaja BA, Sabir F, Qazi S, Mustaqim M. Internet of things (IoT) for next-generation smart systems: A review of current challenges, future trends and prospects for emerging 5G-IoT scenarios. IEEE access. 2020 Jan 28;8:23022-40.

[69]. Al-Sahaf H, Bi Y, Chen Q, Lensen A, Mei Y, Sun Y, Tran B, Xue B, Zhang M. A survey on evolutionary machine learning. Journal of the Royal Society of New Zealand. 2019 Jun;49(2):205-28.

[70]. Prakash C, Kumar R, Mittal N. Recent developments in human gait research: parameters, approaches, applications, machine learning techniques, datasets and challenges. Artificial Intelligence Review. 2018 Jan;49(1):1-40.

[71]. Ahmed I, Jeon G, Piccialli F. From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where. IEEE transactions on industrial informatics. 2022 Jan 27;18(8):5031-42.

[72]. Zhao T, Wang S, Ouyang C, Chen M, Liu C, Zhang J, Yu L, Wang F, Xie Y, Li J, Wang F. Artificial intelligence for geoscience: Progress, challenges, and perspectives. The Innovation. 2024 Sep 9;5(5).

ISSN : 3079-5761
Volume 2, Number 4, 2026
https://doi.org/10.70445/gtst.2.4.2026.1-23

[73]. Bolón-Canedo V, Morán-Fernández L, Cancela B, Alonso-Betanzos A. A review of green artificial intelligence: Towards a more sustainable future. Neurocomputing. 2024 Sep 28;599:128096.

[74]. Angelis D, Sofos F, Karakasidis TE. Artificial Intelligence in Physical Sciences: Symbolic Regression Trends and Perspectives: D. Angelis et al. Archives of Computational Methods in Engineering. 2023 Jul;30(6):3845-65.

[75]. Mahmud M, Kaiser MS, Hussain A, Vassanelli S. Applications of deep learning and reinforcement learning to biological data. IEEE transactions on neural networks and learning systems. 2018 Jan 31;29(6):2063-79.

[76]. Haenlein M, Kaplan A. A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. California management review. 2019 Aug;61(4):5-14.

[77]. Ooi KB, Tan GW, Al-Emran M, Al-Sharafi MA, Capatina A, Chakraborty A, Dwivedi YK, Huang TL, Kar AK, Lee VH, Loh XM. The potential of generative artificial intelligence across disciplines: Perspectives and future directions. Journal of Computer Information Systems. 2025 Jan 2;65(1):76-107.

[78]. Benavides-Hernandez J, Dumeignil F. From characterization to discovery: artificial intelligence, machine learning and high-throughput experiments for heterogeneous catalyst design. ACS Catalysis. 2024 Jul 24;14(15):11749-79.

[79]. Jing Y, Bian Y, Hu Z, Wang L, Xie XQ. Deep learning for drug design: an artificial intelligence paradigm for drug discovery in the big data era. The AAPS journal. 2018 Mar 30;20(3):58.

[80]. Sujith AV, Sajja GS, Mahalakshmi V, Nuhmani S, Prasanalakshmi B. Systematic review of smart health monitoring using deep learning and Artificial intelligence. Neuroscience informatics. 2022 Sep 1;2(3):100028.