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AI-DRIVEN PREDICTIVE MAINTENANCE FOR ROAD TRANSPORT INFRASTRUCTURE

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Abstract
Predictive maintenance is transforming vehicle and infrastructure management by reducing costs and downtime in intelligent transportation systems. This study explores the application of AI in smart transport to anticipate equipment failures and optimize repair schedules. Using real-time sensor data, predictive algorithms—such as neural networks—identify issues before they lead to costly breakdowns. Unsupervised learning enables real-time anomaly detection, while supervised models analyze historical maintenance data for patterns. AI-powered predictive maintenance supports a shift from reactive to proactive practices, enhancing efficiency, safety, and reliability. The study also examines its integration within IoT-connected smart cities, addressing challenges like data integration, algorithm scalability, and cybersecurity. Findings suggest AI can significantly improve operational efficiency, lower maintenance costs, and reduce system disruptions in modern transportation networks.

INTRODUCTION

The administration and Maintenance of transportation infrastructures and vehicles are going through a paradigm shift as a result of the modern transportation system's increasing complexity and the increased expectations for sustainability, safety, and efficiency. The intricacies of today's interconnected networks have proven too difficult for traditional approaches to transport network maintenance, which are based on reactive (fix it after it happens) or preventative (repair it occasionally) maintenance techniques. These challenges include considerable running costs, idle periods, and unplanned malfunctions that could disrupt the functioning of important systems [1].

The convergence of multiple emerging technologies is essential to smart transportation systems. Among the technologies covered are big data analytics, cloud computing, artificial intelligence, and the internet of things. Thanks to these technologies, all modes of transportation from cars and trains to aircraft and trains can now share and take into account data in real time. In order to provide more effective, secure, and ecologically friendly transportation infrastructures, smart transportation combines digital and physical resources. For instance, vast volumes of traffic data, vehicle performance data, and infrastructure dependability data may be obtained via IoT sensors on roads, bridges, and automobiles. Using AI systems to analyze this data could improve traffic flow, save energy consumption, and forecast maintenance needs [2]. The development of AI and IoT technology is accelerating from traditional to smart transportation systems. Machine learning, deep learning, and artificial intelligence have advanced to the point where they can now analyze vast volumes of data in real time, spot trends, and make predictions.

This ability is especially helpful for predictive maintenance, as AI can predict when and where faults will occur, preventing costly disruptions and malfunctions [3]. More advanced, data-driven solutions that can anticipate and stop possible malfunctions are desperately needed as smart transportation systems develop. Here, AI and predictive maintenance come in handy. In order to keep transportation systems operating smoothly, predictive maintenance uses artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) to optimize maintenance programs using real-time monitoring and failure prediction data [1]. Compared to traditional monitoring techniques, AI-driven predictive maintenance can greatly reduce total downtime and asset lifetime while enabling alarms to be sent out instantly to address previously undetectable trends or irregularities in system functioning. Predictive maintenance is therefore essential for smart city and transportation network infrastructure, as it guarantees significant cost savings, increased dependability, and improved safety.

Predictive maintenance solutions powered by AI seek to identify wear and tear or impending issues as soon as possible by continuously monitoring the state of transportation assets. These systems gather data from a variety of sources, such as Internet of Things (IoT) sensors, maintenance logs, and ambient conditions. Through the use of computer learning algorithms, the data is filtered in order to find trends and predict when repairs may be necessary [4].

The ability to change maintenance operations from a time-based schedule to a condition-based strategy is one of the major benefits of predictive maintenance. Conventional preventative maintenance entails providing vehicles and facilities at predetermined intervals, irrespective of their general state. Nevertheless, this approach often results in either excessive maintenance, which is expensive, or insufficient maintenance, which raises the likelihood of failure. Conversely, predictive maintenance makes use of real-time data collection to determine when maintenance is essential in order to avoid needless repairs and unforeseen malfunctions [5]. The high stakes for both safety and economic considerations make transportation systems a prime choice for AI-driven predictive maintenance. In railroad networks, in order to identify issues with track geometry, wheel rail interactions, or braking systems, artificial intelligence (AI) can analyze data from train and track sensors. AI may also monitor components like tires, motors, and brakes in the transportation sector to determine whether they require maintenance, preventing issues for drivers while they are operating a vehicle [6]. Predictive maintenance solutions driven by big data analytics, the internet of things (IoT), machine learning (DL), and artificial intelligence (AI) serve as the foundation for these systems. These technologies work together to gather, process, and analyze data in order to give transportation operators relevant information.

The implementation of predictive maintenance relies heavily on machine learning techniques. These algorithms search for patterns in both historical and current data and apply the predictions they find. Decision trees and random forests are common examples of supervised learning techniques used to categorize problems and forecast failures. Transportation systems also employ unsupervised learning techniques like clustering and anomaly detection to spot questionable activities that might point to an impending breakdown [7]. When dealing with large amounts of unstructured data, such as sensor readings or images, deep learning (DL), a subfield of machine learning, excels. In order to examine sensor data, spot irregularities, and provide extremely accurate failure predictions, predictive maintenance systems have employed CNNs and RNNs [8]. Real-time data from transportation systems can be gathered using Internet of Things (IoT) devices like sensors and actuators.

These tools are crucial for assessing the state of vehicles and infrastructure since they monitor variables including load, vibration, temperature, and pressure. Artificial intelligence (AI) algorithms examine data collected by Internet of Things (IoT) devices and transmitted to cloud platforms [9]. To make sense of the enormous amounts of data produced by the Internet of Things, smart transportation systems require sophisticated data processing and analysis techniques. objects (IoT) gadgets. To handle, evaluate, and process this data in real time, big data analytics systems which are frequently hosted in the cloud are required. These systems efficiently handle and analyze large volumes of data by utilizing distributed computing techniques like Spark and Hadoop [11].

Predictive maintenance using AI in smart transportation systems has a lot of potential, but in order for it to be achieved, a few obstacles must be removed.

Transportation systems become data rich and possibly knowledge poor as a result of the significant difficulty of integrating numerous data sources. Consistent usage of data formats and protocols is necessary for incorporating this information into a comprehensive predictive maintenance system [10]. The scalability of artificial intelligence algorithms is another barrier to scalability. The demand for data processing is growing exponentially as a result of transportation networks' growing size and complexity. Accuracy and performance shouldn't be crucial factors in the development of AI systems that process large amounts of data. In addition, because predictive maintenance systems are often linked to susceptible transportation infrastructures, their cybersecurity needs to be updated [12]. Predictive maintenance driven by AI, however, will be extremely beneficial for intelligent transportation systems. Transportation operators will be better equipped to anticipate and prevent problems when they combine it with big data analytics and the continuous advancement of AI. Furthermore, as smart cities and autonomous cars gain popularity, transportation networks will require AI-driven predictive maintenance. The more data they save, the more important AI-driven predictive maintenance will be in ensuring everyone's safety [13].

Various Maintenance Strategies

Maintenance strategies, also known as maintenance policies in the literature, cover maintenance tasks like replacing, renewing, and repairing parts that are necessary to maintain the enterprise's assets' health status over time and to carry out its operational duties. Numerous scholars have classed maintenance strategies in various ways. Four general maintenance procedures are frequently cited in the literature: maintenance that is prescriptive, corrective, predictive, and preventative [30].

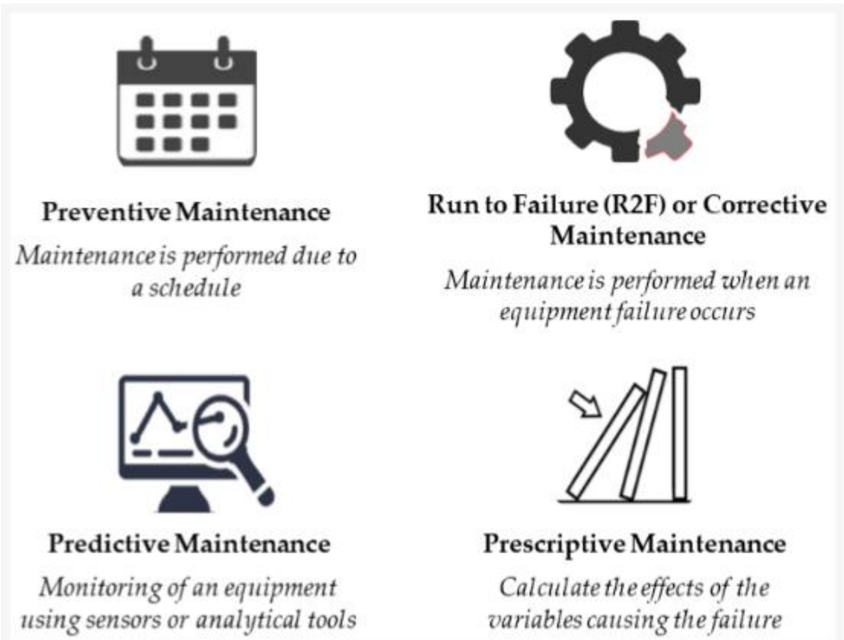

Figure 1: The working techniques of different types of maintenance [30].

The practice of organizing and carrying out maintenance tasks utilizing a variety of forecasting techniques for probable problems prior to their occurrence is known as predictive maintenance. Data science is used in PdM activities to forecast equipment failures. The data is used to determine the defect point so that maintenance can be scheduled ahead of time. By scheduling the maintenance procedure at the best time before the equipment's life expires, the goal is to ensure the system's sustainability [31]. Deep ideas and artificial intelligence provide numerous vital functions in various domains. The idea of deep learning, in particular, guarantees that significant and relevant conclusions are drawn from big data sets [32]. Non-damaging testing procedures that monitor and gather real-time data of equipment through sensors, such as acoustic, infrared, sound level, oil analysis, vibration analysis, and thermal image recognition, are encouraged by predictive maintenance strategies.

The most fundamental component of predictive maintenance activities is the classification of sensor data using artificial intelligence (AI) or statistical approaches to estimate when the equipment will break [33]. Routine maintenance tasks can be tailored to the requirements of each piece of equipment in the system by utilizing AI in predictive maintenance tasks. With the help of historical failures and associated data, AI can be trained to anticipate when future failures will occur. Artificial intelligence (AI) can quickly predict when equipment will break and instantly identify abnormalities in equipment, avoiding unplanned production disruptions [34]. The idea of predictive maintenance has gained popularity and has been applied often. Predictive maintenance forecasts offer numerous advantages, including a reduction in unplanned outages, an increase in equipment efficiency, a reduction in expenses by preventing needless maintenance, a reduction in breakdowns, an increase in occupational safety, and a maximization of actual production time [30, 35].

AI Driven to Predict Maintenance:

In terms of predictive maintenance, artificial intelligence (AI) capabilities obviously surpass more conventional methods such as condition-based monitoring and preventative maintenance. By analyzing large datasets in real time and forecasting when equipment is likely to break down, AI models based on machine learning and deep learning can minimize unplanned downtime and associated costs. To anticipate the lifespan of car parts, researchers proposed deep learning methods, demonstrating how AI may improve predictive maintenance. Their research indicates that AI can lower maintenance costs while increasing system reliability [14]. The advantages of neural network-driven predictive maintenance were also examined by Johnson, who discovered that real-time data collecting using Internet of Things (IoT) sensors was beneficial. It was an impressive confirmation of the high accuracy with which AI-driven solutions can foresee the collapse of complex systems, like railroads, which are extremely difficult to predict due to their many interdependent components.

AI models are becoming more and more significant in predictive maintenance as these models develop, particularly when real-time predictive work is required because analysis and decision-making can only be done using the data that is already available. [15]. Based on research that has demonstrated the value of using deep learning algorithms for predictive maintenance, artificial intelligence (AI) can be used to predict the lifespan of vehicle components in smart transportation systems. But their results also demonstrate how AI may lower maintenance costs and increase system reliability. Furthermore, the merits and cons of using neural network-based predictive maintenance were studied, as well as the potential benefits of real-time battery and sensor data collecting. The Internet of Things (IoT) sensors will be used to handle this. However, their research revealed that AI-based solutions could accurately anticipate the collapse of complex systems like railroads, which are notoriously difficult to predict due to their many interrelated pieces [1].

Methods for Machine Learning

Numerous machine learning techniques have been used to accomplish predictive maintenance tasks in transportation networks. For instance, supervised learning models like support vector machines, decision trees, and random forests are typically used for failure classification and prediction. If you have labeled data to train on, supervised learning models work effectively. Predictive maintenance is then carried out. Decision trees were used in a smart train system in 2012 to precisely identify when and where repairs were required based on historical failure data [16]. When there is little to no labeled data, unsupervised learning methods like anomaly detection and clustering algorithms are increasingly being used in predictive maintenance. Without knowing in advance what kinds of problems can occur, anomaly detection algorithms are able to identify maintenance-related signals in data from transportation systems. It is showed in another research that the potential of unsupervised machine learning for real-time vehicle health monitoring and fault diagnosis by using k-means clustering for anomaly detection in automotive systems [17]. A subfield of machine learning called deep learning has greatly enhanced predictive maintenance skills by making it possible to analyze vast amounts of unstructured data, including sensor data, images, and videos. The prediction and categorization of problems in RNNs and CNNs is a common use case in the field of predictive maintenance. It has been demonstrated that CNNs, using sensor data from smart transportation systems, can reliably and precisely predict when maintenance is required [18].

Short introduction to the Internet of Thing

Predictive maintenance in intelligent transportation systems has been made easier by IoT. IoT sensors gather data in real time from environmental, transportation, and infrastructure variables to feed AI algorithms that allow for accurate predictions. Compared to earlier times, transportation systems can now identify their malfunctions and stop additional problems with the use of artificial intelligence and the Internet of Things.This is because sensor data may be continuously processed and monitored to search for anomalies or degradation [19]. Existing predictive maintenance systems become even more complex when real-time data from multiple sources is added via the Internet of Things (IoT).

To guarantee that the AI models can process and analyze the data in a way that benefits the system, complex data integration techniques are required [19]. When they look at how data from various Internet of Things (IoT) devices might be integrated into a smart city transportation network, they stress the necessity of widely recognized communication protocols and data formats. They contributed to the creation of powerful predictive maintenance solutions by focusing on how to combine data from various sources and scale the expansion of IoT networks [20]. Additionally, an AI-driven predictive maintenance approach that transitions from a time-based maintenance schedule to a condition-based maintenance strategy (driven by the present asset status) can be fueled by real-time data [20]. This approach offers a significant improvement in terms of system efficiency and significantly lowering unnecessary maintenance. Researchers have shown that condition-based maintenance facilitated by the Internet of Things (IoT) can reduce maintenance costs in smart transportation systems by 30% [21].

Algorithms and Efficient Scalability

Predictive maintenance solutions' scalability is becoming increasingly crucial as smart transportation systems get more complex. Traditional data processing systems may get overloaded by the ever-increasing volume of data generated by Internet of Things (IoT) sensors.

The scalability of artificial intelligence models used in transportation predictive maintenance was modeled in order to address the data-intensive needs of contemporary transportation systems, and it was determined that distributed computing architectures are necessary [22]. As a result of cloud computing's capacity to analyze and compile large datasets online, the scalability issue has been resolved. Numerous studies have lauded cloud-based predictive maintenance solutions that use cloud-deployed AI algorithms to analyze sensor data and provide maintenance suggestions. It showed how the amount of Internet of Things (IoT) devices and data streams could expand their cloud-based predictive maintenance solution for a metropolitan transportation network [23]. The efficiency of AI algorithms is a significant factor in scalability as well. The AI model's computational complexity increases with the amount of data you have. Effective algorithm design is essential to guaranteeing real-time, delay-free performance from predictive maintenance systems. It investigated ways to enhance the models utilized in predictive maintenance AI in order to reduce computing overhead while preserving accuracy [24].

Table 1: Various technology uses in Traffic safety and maintenance.

No	Technologies	Role of technology maintenance	References
1.	**Autonomous Vehicles**	An innovative technology advancement that has the potential to revolutionize transportation in the future is autonomous cars. With the help of sophisticated sensors and artificial intelligence, these self-driving cars can function with little to no human involvement, opening the door to safer, more effective, and sustainable urban mobility.	[36]

2.	**Enhanced Safety**	AVs with AI systems are able to interpret information more quickly and correctly than humans, which results in faster reaction times and fewer accidents. The number of traffic fatalities and injuries might be significantly decreased by this move toward machine-driven decision-making.	[37]
3.	**Light Detection and Ranging (LiDAR)**	Hardware and software work together to help autonomous cars negotiate challenging traffic situations. With the use of LiDAR (Light Detection and Ranging), radar, cameras, GPS, and advanced artificial intelligence algorithms, autonomous vehicles (AVs) are able to scan their environment in real time. These sensors give cars 360-degree vision and allow them to recognize and respond to pedestrians, other cars, and objects. In order for AVs to plan routes, make snap judgments, and carry out driving functions including braking, steering, and acceleration, artificial intelligence (AI) is essential to analyzing the data gathered by these sensors.	[38]
4.	**Real-Time Traffic Monitoring**	AI analyzes data from several sources, such as road cameras, sensors, linked cars, and GPS devices, to provide real-time traffic status monitoring. By eliminating jams and enhancing overall traffic flow, this real-time knowledge gives traffic managers the means to respond quickly and efficiently.	[39]
5.	**Dynamic Signal Control**	Dynamic signal control, which improves traffic light timings based on real-time data, is made possible by AI integration. Signal patterns can be modified by AI algorithms in reaction to shifting pedestrian traffic, traffic volumes, or emergency vehicle needs. This flexibility lowers needless pauses, increases fuel efficiency, and shortens wait times at junctions.	[40]
6.	**Incident Detection and Management**	AI can swiftly spot odd occurrences that might point to an accident or obstacle, including a sudden slowing or stalled cars. Once identified, the technology may concurrently reroute traffic to prevent additional blocking and notify emergency services and traffic operators. Road safety is increased when problems are detected early, as this lessens their effect and lowers the number of secondary collisions.	[41]
7.	**Route Optimization Through AI**	Modern transportation systems must optimize their routes, especially as the population of cities increases and traffic becomes a constant problem. By evaluating enormous volumes of data to identify the most effective routes for cars, artificial intelligence (AI) significantly improves route optimization.	[42]
8.	**Data-Driven Decision Making**	AI-powered route optimization depends on a multitude of data gathered from several sources, such as real-time weather data, GPS devices, traffic sensors, and historical traffic patterns. By combining this data, artificial intelligence (AI) algorithms are able to assess a variety of variables, including traffic patterns, road closures, collisions, and even pedestrian activity, in order to recommend the most effective routes for vehicles.	[43]

Challenges and Future Prospects of AI-Driven Predictive Maintenance in Smart Transportation Systems

Despite the significant advancements in AI-driven predictive maintenance, certain challenges remain to be addressed. Due to the high vulnerability of these networks to assaults, the Internet of Things (IoT) has numerous vulnerabilities, particularly with regard to data security and privacy [25]. Predictive maintenance solutions need to be secure because transportation systems are susceptible to data breaches and disruptions [26]. The authentication and encryption techniques were developed to safeguard AI models and Internet of Things (IoT) devices. This led to the realization of the significance of cybersecurity in predictive maintenance systems [1]. Making AI models comprehensible is the second challenge. Despite the predictive maintenance task's high accuracy, transportation operators have trouble comprehending how these "black box" algorithms arrive at their conclusions. The implementation of AI-based predictive maintenance systems may be hampered by the confidentiality. In order to address this issue and increase the credibility of AI-generated recommendations, it developed interpretable machine learning models that provide an explanation for a forecast [27].

AI-driven predictive maintenance has a very promising future in spite of all these obstacles. Better, more scalable, and safer predictive maintenance systems will be achievable as big data analytics, the internet of things, and artificial intelligence (AI) algorithms develop. As networks become increasingly autonomous and interconnected, predictive maintenance (PM) will be crucial to guaranteeing the safety, dependability, and sustainability of smart transportation systems [1]. Over the past ten years, there has been a lot of interest in the application of AI to predictive maintenance for smart transportation systems. Here, we review some of the major developments in AI-driven predictive maintenance, machine learning techniques, IoT integration, and how these technologies aren't always scalable or simple to use. In order to construct smart transportation systems that are more reliable, safe, and efficient, each of these areas is crucial [28]. We can all agree that artificial intelligence (AI) is revolutionizing predictive maintenance when compared to more traditional methods like condition-based monitoring and preventative maintenance. AI models, namely those based on machine learning and deep learning, can anticipate when equipment would malfunction, minimizing unplanned downtime and operational costs [29].

Methods involved in Machine Learning

In the context of transportation systems, a variety of machine learning techniques have been applied to predictive maintenance tasks. To this goal, for example, models for failure classification and prediction such support vector machines, decision trees, and, in particular, random forests are frequently employed. If labeled data is available for training, this is advantageous; if not, unsupervised learning models are used. Decision trees were utilized to modify the approach since smart railway systems have already been used to accurately forecast failure sites where repair was required after evaluating historical failure data. Predictive maintenance is increasingly using unsupervised learning techniques like anomaly detection and clustering algorithms, especially when there is a lack of labelled data.

Algorithms for anomaly detection may identify trends in transportation system data that indicate maintenance needs without anticipating the kind of problems that might occur. The k-means clustering unsupervised machine learning anomaly detection technique provided real-time vehicle health monitoring and fault identification [1].

Predictive maintenance capabilities have been significantly enhanced by deep learning, a subfield of machine learning that makes it possible to analyze vast amounts of unstructured data, including sensor data, images, and videos. Common applications in predictive maintenance include the prediction and classification of faults in RNNs and CNNs, as well as the utilization of sensor data from smart transportation systems to demonstrate the accuracy and dependability of the forecasting of when maintenance is required [29].

Conclusion:

In order to keep modern transportation systems in optimal operating condition, it is necessary to adopt a sound engineering approach and apply appropriate and timely maintenance techniques. Predictive maintenance, when combined with the Internet of Things (IoT) and used in smart transportation systems, can offer a revolutionary approach to asset management in contrast to more traditional reactive and preventative methods. Predictive maintenance can lower operating costs, increase maintenance efficiency, and decrease downtime by utilizing real-time data from Internet of Things (IoT) sensors and

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advanced analytics. In contrast to reactive maintenance, which leads to expensive emergency repairs and reactive maintenance that wastes service, predictive maintenance maximizes resource efficiency and operational uptime by scheduling repairs based on an actual asset condition state. Unsupervised learning techniques like anomaly detection and clustering algorithms are gaining traction in predictive maintenance, particularly when labeled data is scarce. Algorithms for anomaly detection may identify trends in transportation system data that suggest maintenance is required without knowing earlier what kind of problems are conceivable.

REFERENCES:

[1] S. Hundekari, T. Mittal, A. Dutt, M. Bhavana, R. Kumar, and G. Nijhawan, "AI-driven solutions for predictive maintenance in smart transportation systems," in *2025 Int. Conf. Comput., Commun. Inf. Technol. (ICCCIT)*, Feb. 7, 2025, pp. 572–577.

[2] P. William, N. Chinthamu, I. Kumar, M. Gupta, A. Shrivastava, and A. P. Srivastava, "Schema design with intelligent multi modelling edge computing techniques for industrial applications," in *2023 3rd Int. Conf. Pervasive Comput. Soc. Netw. (ICPCSN)*, Salem, India, 2023, pp. 1280–1285, doi: 10.1109/ICPCSN58827.2023.00215.

[3] S. K. Swarnkar, A. Sharma, J. Somasekar, and B. Bhushan, *Machine Learning in Multimedia: Unlocking the Power of Visual and Auditory Intelligence*, CRC Press, 2024, pp. 1–154.

[4] A. Bani Ahmad, P. William, D. Uike, A. Murgai, K. K. Bajaj, A. Deepak, and A. Shrivastava, "Framework for sustainable energy management using smart grid panels integrated with machine learning and IoT-based approach," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 2s, pp. 581–590, 2023.

[5] A. Deepak, P. William, R. Dubey, S. Sachdeva, C. Vinotha, S. Masand, and A. Shrivastava, "Impact of artificial intelligence and cyber security as advanced technologies on bitcoin industries," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 3s, pp. 131–140, 2023.

[6] D. R., V. S. Biradar, M. V., C. Singh, A. Deepak, and A. Shrivastava, "Energy-efficient resource allocation and relay-selection for wireless sensor networks," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 5s, pp. 113–121, 2023.

[7] S. Venkatesh, S. P. Kori, P. William, M. L. Meena, A. Deepak, D. S. Hasan, and A. Shrivastava, "Data reduction techniques in wireless sensor networks with Internet of Things," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 8s, pp. 81–92, 2023.

[8] P. William, A. Poornashankar, A. Shrivastava, N. Tripathi, A. Anil, and A. Singh, "Secure authentication protocols for Internet of Things (IoT) devices," in *2023 6th Int. Conf. Contemp. Comput. Informatics (IC3I)*, Gautam Buddha Nagar, India, 2023, pp. 1569–1574.

[9] P. William, A. K. Rai, P. Madan, C. P. Kumar, A. Shrivastava, and A. Rana, "Analysis of blockchain technology to protect data access using intelligent contract mechanism for 5G networks," in *2023 6th Int. Conf. Contemp. Comput. Informatics (IC3I)*, Gautam Buddha Nagar, India, 2023, pp. 1651–1657.

[10] P. William, S. Kumar, A. Gupta, A. Shrivastava, A. L. N. Rao, and V. Kumar, "Impact of green marketing strategies on business performance using big data," in *2023 4th Int. Conf. Comput., Autom. Knowl. Manag. (ICCAKM)*, Dubai, UAE, 2023, pp. 1–6.

[11] P. William, A. Agrawal, N. Rawat, A. Shrivastava, A. P. Srivastava, and A. Ashish, "Enterprise human resource management model by artificial intelligence digital technology," in *2023 4th Int. Conf. Comput., Autom. Knowl. Manag. (ICCAKM)*, Dubai, UAE, 2023, pp. 1–6.

[12] P. William, A. Panicker, A. Falah, A. Hussain, A. Shrivastava, and A. K. Khan, "The emergence of artificial intelligence and machine learning in contemporary business management," in *2023 4th Int. Conf. Comput., Autom. Knowl. Manag. (ICCAKM)*, Dubai, UAE, 2023, pp. 1–6.

[13] P. William, G. Sharma, K. Kapil, P. Srivastava, A. Shrivastava, and R. Kumar, "Automation techniques using AI-based cloud computing and blockchain for business management," in *2023 4th Int. Conf. Comput., Autom. Knowl. Manag. (ICCAKM)*, Dubai, UAE, 2023, pp. 1–6.

[14] C. Nayak, P. William, R. Kumar, A. Deepak, K. Yadav, A. L. N. Rao, A. Srivastava, and A. Shrivastava, "Edge cloud server deployment with machine learning for 6G Internet of Things," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 16s, p. 328, 2024.

[15] S. K. Swarnkar and A. Ambhaikar, "Improved convolutional neural network based sign language recognition," *Int. J. Adv. Sci. Technol.*, vol. 27, no. 1, pp. 302–317, 2019.

[16] D. Singh, A. Rana, M. Memoria, S. K. Shah, A. Gupta, and R. Kumar, "Design of a 12 phase VCO with stacked CNTFETs and provision to improve performance by lowering the number of metallic tubes," in *Int. Conf. Numer. Anal. Appl. Math. ICNAAM 2021*, AIP Conf. Proc., 2023, pp. 1–4.

[17] K. Joshi, V. K. Bhagat, H. Anandaram, R. Kumar, A. Gupta, and K. Hari Krishna, "A review approach on deep learning algorithms in computer vision," in *Intell. Syst. Appl. Comput. Vision*, N. Mittal, A. K. Pandit, M. Abouhawwash, and S. Mahajan, Eds., CRC Press, 2023, pp. 1–15.

[18] A. Gupta, R. K. Singh, J. Paul, M. Sharma, and S. Joshi, "Battery-operated electric vehicles (BOEVs) adoption in India: Analysis of barriers and strategies," *IEEE Trans. Eng. Manage.*, vol. 71, pp. 7076–7087, 2024.

[19] S. Tyagi, A. Gupta, and N. Ansari, "Adoption and perception of banking customers towards green mode of banking: A demonstration of structural equation modelling," *J. Financ. Serv. Market.*, pp. 1–17, 2023.

[20] H. Sharma, H. Kumar, A. Gupta, and M. A. Shah, "Computer vision in manufacturing: A bibliometric analysis and future research propositions," *Int. J. Adv. Manuf. Technol.*, vol. 127, pp. 5691–5710, 2023.

[21] O. Gupta, P. Joshi, and A. Gupta, "Prioritizing the enablers for adoption of AI-based health care wearables among elderly people," in *2023 4th Int. Conf. Intell. Eng. Manag. (ICIEM)*, London, UK, 2023, pp. 1–4.

[22] A. Gupta, C. N., J. Jha, A. Sayal, V. Gupta, and M. Memoria, "Machine learning algorithms for disease diagnosis using medical records: A comparative analysis," in *2023 4th Int. Conf. Intell. Eng. Manag. (ICIEM)*, London, UK, 2023, pp. 1–6, doi: 10.1109/ICIEM59379.2023.10165850.

[23] S. K. Swarnkar, A. Ambhaikar, V. K. Swarnkar, and U. Sinha, "Optimized convolution neural network (OCNN) for voice-based sign language recognition: Optimization and regularization," *Lecture Notes Netw. Syst.*, vol. 191, pp. 633–639, 2022.

[24] R. K. Navandar, V. R. Gosavi, S. K. Swarnkar, R. S. S. Varma, T. B. Patil, and D. G. Bhalke, "Statistical signal processing for radar systems," *Panamerican Math. J.*, vol. 35, no. 1S, pp. 200–209, 2025.

[25] A. Banik and A. Sengupta, "Irrigation pumping scheme based on solar PV and zeta converters with PMBLDC motor," in *Recent Advances in Manufacturing Modelling and Optimization*, S. Kumar, J. Ramkumar, and P. Kyratsis, Eds., Springer, Singapore, 2022, pp. 1–12, doi: 10.1007/978-981-16-9952-8_46.

[26] Y. T. Singh, B. Chettri, A. Banik, K. O. Obodo, and D. P. Rai, "Carbon and boron nitride nanostructures for hydrogen storage applications; a theoretical perspective," *Adv. Mater. Nano Syst.: Theory Exper.*, pp. 1–32, 2025, doi: 10.2174/9789815050745122010004.

[27] A. Es-Smairi, N. Fazouan, E. Maskar, I. Bziz, M. Sabil, A. Banik, and D. P. Rai, "Rare earth (Tm, Y, Gd, and Eu) doped ZnS monolayer: A comparative first-principles study," *Electron. Struct.*, vol. 6, no. 1, p. 015001, Jan. 2024, doi: 10.1088/2516-1075/ad17d5.

ISSN: 3106-7840 | 3106-7832
Volume 2, Issue 2, 2025

[28] S. Thangamayan, M. D. Walunjkar, D. K. Ray, M. Venkatesan, A. Banik, and K. P. Amrutkar, "5G modulation technique comparisons using simulation approach," in *Proc. 2022 3rd Int. Conf. Intell. Eng. Manag. (ICIEM)*, London, UK, Apr. 2022.

[29] H. R. Devarajan, S. Balasubramanian, S. K. Swarnkar, P. Kumar, and V. R. Jallepalli, "Deep learning for automated detection of lung cancer from medical imaging data," 2023.

[30] O. Ersöz, İ. F. İnal, A. Aktepe, A. K. Türker, and S. Ersöz, "A systematic literature review of the predictive maintenance from transportation systems aspect," *Sustainability*, vol. 14, no. 21, p. 14536, 2022.

[31] I. Mallouk, Y. Sallez, and B. A. El Majd, "Machine learning approach for predictive maintenance of transport systems," in *Proc. 2021 3rd Int. Conf. Transp. Smart Technol.*, Tangier, Morocco, May 27–28, 2021.

[32] B. Zwolińska and J. Wiercioch, "Selection of maintenance strategies for machines in a series-parallel system," *Sustainability*, vol. 14, p. 11953, 2022.

[33] O. Serradilla, E. Zugasti, J. Rodriguez, and U. Zurutuza, "Deep learning models for predictive maintenance: A survey, comparison, challenges and prospects," *Appl. Intell.*, vol. 52, pp. 10934–10964, 2022.

[34] V. Cusati, S. Corcione, and V. Memmolo, "Potential benefit of structural health monitoring system on civil jet aircraft," *Sensors*, vol. 22, p. 7316, 2022.

[35] J. P. Usuga-Cadavid, S. Lamouri, B. Grabot, and A. Fortin, "Using deep learning to value free-form text data for predictive maintenance," *Int. J. Prod. Res.*, vol. 60, pp. 4548–4575, 2021.

[36] V. Bhardwaj, "AI-enabled autonomous driving: Enhancing safety and efficiency through predictive analytics," *Int. J. Sci. Res. Manage. (IJSRM)*, vol. 12, no. 02, pp. 1076–1094, 2024.

[37] X. Chen and E. Olson, "AI in transportation: Current developments and future directions," *Innov. Comput. Sci. J.*, vol. 8, no. 1, 2022.

[38] X. Chen, T. Ryan, and H. Wang, "Exploring AI in education: Personalized learning, automated grading, and classroom management," *MZ Comput. J.*, vol. 3, no. 1, 2022.

[39] S.-H. Chung, "Applications of smart technologies in logistics and transport: A review," *Transp. Res. Part E: Logist. Transp. Rev.*, vol. 153, p. 102455, 2021.

[40] P. Arévalo, D. Ochoa-Correa, and E. Villa-Ávila, "A systematic review on the integration of artificial intelligence into energy management systems for electric vehicles: Recent advances and future perspectives," *World Electr. Veh. J.*, vol. 15, no. 8, p. 364, 2024.

[41] K. Ivanova, "A review of deep learning applications in energy-efficient transportation systems," *Int. J. Intell. Autom. Comput.*, vol. 5, no. 2, pp. 15–28, 2022.

[42] S. Malik, H. A. Khattak, Z. Ameer, U. Shoaib, H. T. Rauf, and H. Song, "Proactive scheduling and resource management for connected autonomous vehicles: A data science perspective," *IEEE Sensors J.*, vol. 21, no. 22, pp. 25151–25160, 2021.

[43] M. V. Selvi, P. Upadhyay, A. Revathi, N. Punitha, and M. Saravanakumar, "Enhancing urban AI-powered transportation systems with machine learning," in *Urban Mobility and Challenges of Intelligent Transportation Systems*, IGI Global, 2025, pp. 363–382