Library Progress International *Print version ISSN 0970 1052*
Vol.44 No. 3, Jul-Dec 2024: P. 16435-16441 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

Transforming Predictive Maintenance in Automotive Systems through Big Data and Data Mining Techniques

Sukhpreet Singh[1], Dr Ashwani Sethi[2]

[1]Research Scholar, Guru Kashi University, Talwandi Sabo, Bathinda, Punjab
sukhis005@gmail.com
[2]Professor, Guru Kashi University, Talwandi Sabo, Bathinda, Punjab
drashwanisethi@gku.ac.in

How to cite this article: Sukhpreet Singh, Ashwani Sethi (2024) Transforming Predictive Maintenance in Automotive Systems through Big Data and Data Mining Techniques. *Library Progress International,* 44(3), 16435-16441

Abstract. Effective maintenance practices are essential for reducing equipment failures and minimizing disruptions in production, especially in the automotive industry. Predictive maintenance has emerged as a proactive approach to detect potential equipment issues before they result in breakdowns, improving both safety and cost efficiency. By harnessing big data and advanced analytics, predictive maintenance benefits from real-time data processing and more informed decision-making. This paper examines the role of big data in enhancing predictive maintenance strategies within the automotive sector, highlighting the significance of historical data and the use of various analytical techniques. The integration of predictive maintenance with a big data framework transforms maintenance operations by boosting asset reliability, reducing downtime, and achieving substantial cost reductions. Predictive insights enable automotive companies to take preemptive maintenance actions, improving operational performance, customer satisfaction, and competitive positioning. This paper presents predictive maintenance methodologies, big data architecture, maintenance strategies and frameworks, as well as the benefits and future directions of predictive maintenance.
Keywords: Predictive Maintenance, Big Data, Automotive Industry, Maintenance

1. Introduction

Maintenance encompasses all actions required to restore or sustain a system or component in a condition that allows it to perform its designated tasks. The primary goal of maintenance is to preserve system performance and capacity while minimizing the costs related to maintenance operations and lost productivity. Any deviation or change in the system that results in suboptimal performance is considered a failure. Although a small percentage of failures may significantly affect safety and productivity, most lead to expensive downtimes, disruptions, inconveniences, and a decline in quality. The aim of maintenance programs is to reduce or eliminate the occurrence of malfunctions and breakdowns.
In the automotive sector, effective use of resources for maintenance is crucial. Traditionally, maintenance activities were scheduled based on time intervals or in reaction to system failures. However, with the rise of big data analytics, the approach is shifting towards proactive and predictive maintenance strategies. This shift is especially promising for the automotive industry, where unexpected downtime can result in substantial financial losses and customer dissatisfaction. By leveraging vast amounts of data generated by automotive systems, the industry has developed advanced maintenance practices that reduce downtime, enhance scheduled planning, and improve customer satisfaction.

1.1. Definition of Predictive maintenance

Predictive maintenance is an advanced approach that focuses on anticipating equipment or machinery breakdowns by using data analysis and monitoring methods. Instead of adhering to predefined schedules or waiting for systems to fail, this method analyzes historical data, real-time sensor inputs, and complex algorithms to foresee potential issues and identify when maintenance is necessary. By recognizing early indicators of wear and tear or malfunction, companies can plan repairs in advance, minimize unexpected stoppages, and enhance both the performance and lifespan of their machines. The ultimate aim of predictive maintenance is to transition from expensive, reactive repairs to preemptive, cost-efficient upkeep, improving operational performance and lowering maintenance costs.

Here are alternative definitions of predictive maintenance from various sources:
1. Gartner: Predictive maintenance is a strategy that anticipates equipment malfunctions through data insights and machine learning, allowing organizations to refine their maintenance planning and cut down on idle time.
2. IBM: Predictive maintenance relies on IoT sensors and advanced data analysis to keep track of equipment in real time, predicting potential issues and scheduling repairs ahead of time to improve asset performance and reduce expenses.
3. Forrester Research: Predictive maintenance uses historical data along with predictive analytics models and machine learning to forecast equipment failures, helping businesses better allocate resources and increase operational effectiveness.
4. McKinsey & Company: Predictive maintenance employs predictive modeling and data techniques to forecast mechanical failures, enabling companies to take preemptive measures to ensure maximum uptime and lower costs.
5. National Institute of Standards and Technology (NIST): Predictive maintenance is a data-centric approach that applies statistical methods and machine learning to forecast equipment issues and recommend the best times for maintenance, leading to more efficient asset management and improved performance.
6. International Society of Automation (ISA): Predictive maintenance merges monitoring technologies with data analysis to forecast breakdowns, uncover root causes, and streamline maintenance approaches, resulting in higher equipment reliability and less unplanned downtime.

1.2. Types of Maintenance

Maintenance activities are generally divided into three distinct categories:
1. Reactive or Corrective Maintenance (CrM),
2. Preventive Maintenance (PvM), and
3. Predictive Maintenance (PdM).

1. Reactive or Corrective Maintenance (CrM): This approach is focused on fixing equipment after a failure has already occurred. The goal is to repair or replace the damaged components and bring the equipment back to its proper functioning state. This method is unplanned and is usually carried out when the equipment has already broken down.
2. Preventive Maintenance (PvM): In this strategy, maintenance tasks such as inspections, servicing, and parts replacements are scheduled at regular intervals to avoid breakdowns. These actions are taken before any malfunction occurs, based on predetermined schedules. Preventive maintenance is designed to extend the life of the equipment and reduce the chances of unexpected failures.
3. Predictive Maintenance (PdM): This technique aims to foresee equipment issues before they happen by using real-time data, monitoring tools, and analytics. By assessing the actual condition of machinery and anticipating future problems, predictive maintenance allows maintenance teams to carry out necessary repairs or adjustments before breakdowns occur. This method minimizes downtime and helps to optimize performance and cost-efficiency.

2. **Big Data Architecture**

1. Volume: Refers to the immense quantity of data generated from various sources. As data production increases exponentially, traditional database systems have had to evolve to handle petabyte-scale datasets. While increasing storage capacity can meet demands, it can also lead to slow data processing and transfer, necessitating advanced infrastructure like supercomputers or large server systems.
2. Velocity: This characteristic highlights the speed at which data is generated, collected, and processed. With technologies such as sensor networks and real-time data exchanges over the internet, organizations can gather information almost instantaneously. To address challenges effectively, businesses must be able to process incoming data streams swiftly, enabling timely insights and rapid decision-making.
3. Variety: Data now comes in numerous formats, ranging from structured data (like databases) to unstructured data (such as text, images, audio, and video). This diversity presents challenges for analysis, as traditional methods are typically designed for structured formats. Organizations must employ advanced data mining techniques to analyze both structured and unstructured data, allowing for more comprehensive insights that inform decision-making.
4. Veracity: This dimension refers to the reliability and accuracy of the data being analyzed. With vast amounts of data being generated, ensuring its quality is crucial for drawing trustworthy conclusions. High veracity in data allows organizations to make informed decisions based on accurate and credible information.
5. Value: The ultimate goal of leveraging big data is to derive meaningful insights that drive value for organizations. By utilizing advanced analytics techniques, businesses can extract rich information from complex datasets, leading to improved operational efficiency and innovation. Understanding the value of data not only involves statistical analysis but

also encompasses deeper insights that can help organizations identify needs and foster continuous improvement.

These five dimensions together illustrate the complexity and potential of big data, highlighting the importance of advanced techniques in managing and extracting insights from vast datasets.

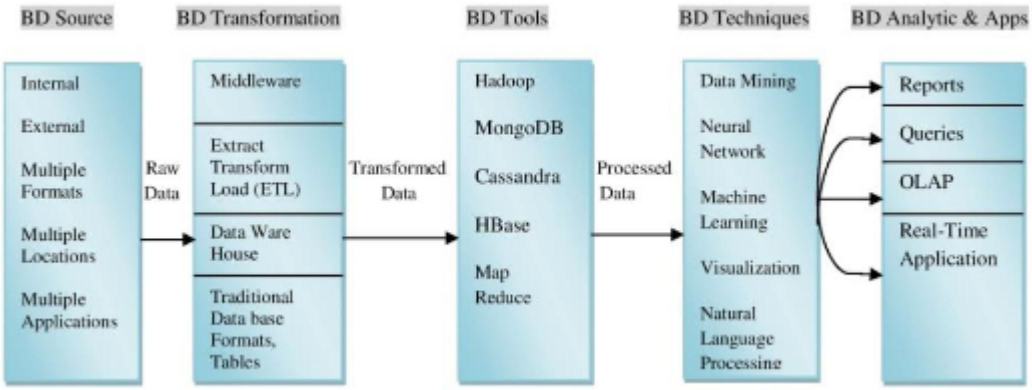

Figure 1. Big Data Architecture Model

3. **Big Data Analytics**

Big Data Analytics involves the examination and interpretation of vast quantities of data to identify trends, relationships, and insights that can inform decision-making and enhance operational performance. In the automotive industry, harnessing Big Data Analytics can lead to substantial improvements in efficiency across various areas. Here are several critical applications of Big Data Analytics:

3.1. Predictive Maintenance

Real-time Sensor Data Assessment: Analyzing information collected from vehicle sensors to anticipate and mitigate potential failures. This encompasses monitoring vital metrics such as engine performance, tire health, and brake wear.

Failure Trend Identification: Employing machine learning techniques to identify signals that typically precede component failures, facilitating timely maintenance interventions.

3.2. Supply Chain Optimization

Demand Prediction: Examining historical sales data alongside market trends to accurately project future demand, which helps maintain optimal inventory levels and minimizes surplus stock.

Logistics Efficiency: Utilizing route optimization strategies to improve logistics operations, thereby reducing delivery times and associated costs.

3.3. Production Line Efficiency

Process Improvement: Reviewing production data to pinpoint bottlenecks and inefficiencies. Implementing enhancements to increase output and shorten cycle times.

Quality Assurance: Applying anomaly detection methods to spot defects in real-time, ensuring that production standards are maintained and waste is minimized.

3.4. Customer Insights and Personalization

Customer Behavior Analysis: Investigating data from customer interactions to gain insights into preferences and behaviors, utilizing sources such as websites, social media, and service centers.

Tailored Marketing: Implementing customer segmentation and targeted marketing strategies to create personalized campaigns that boost engagement and satisfaction.

3.5. Vehicle Design and Innovation

Insights for Product Development: Analyzing market dynamics, customer feedback, and competitor activities to guide vehicle design and innovation, helping to develop features that align with consumer demands and enhance user experience.

Simulation and Testing Enhancements: Leveraging data from simulations and testing processes to improve vehicle safety, performance, and dependability, including data from crash tests, aerodynamic studies, and virtual prototypes.

3.6. Fleet Management

Enhancing Operational Efficiency: Monitoring fleet performance in real-time to optimize routing, fuel efficiency, and maintenance schedules.

Driver Behavior Assessment: Analyzing data related to driver conduct to encourage safe driving habits and reduce accident rates, focusing on metrics such as speed, braking behavior, and compliance with traffic regulations.

3.7. Warranty and Recall Management

Predictive Warranty Assessment: Utilizing predictive analytics to identify potential warranty claims, enabling manufacturers to proactively address issues before they escalate.
Streamlined Recall Processes: Analyzing data to improve recall procedures, ensuring prompt communication with affected customers and efficient resolution of any problems.

4.Tools and Technologies
4.1. Data Warehousing and Processing
Employing frameworks such as Hadoop, Spark, and cloud-based data lakes enables the efficient storage and processing of extensive datasets. These platforms facilitate distributed data processing, allowing organizations to manage petabyte-scale data with enhanced speed and scalability. By leveraging these technologies, companies can streamline data ingestion, ensure rapid access to information, and support complex analytical workloads, thus optimizing overall data management strategies.
4.2. Advanced Analytics and Machine Learning
Integrating sophisticated tools like TensorFlow, Scikit-learn, and SAS allows organizations to execute advanced analytics and develop machine learning models effectively. These platforms support a wide range of analytical techniques, from regression analysis to deep learning, enabling the extraction of actionable insights from large datasets. By utilizing these advanced tools, businesses can create predictive models, enhance data-driven decision-making, and drive innovation through automated analysis.
4.3. Visualization and Reporting
Leveraging data visualization software such as Tableau, Power BI, and D3.js empowers organizations to craft interactive dashboards and detailed reports that facilitate real-time insights. These tools enable users to transform complex data sets into intuitive visual representations, enhancing comprehension and accessibility. By employing effective visualization techniques, businesses can improve their decision-making processes, foster collaboration, and communicate insights more clearly across various stakeholders.

5.Maintenance Strategies
Large volumes of data generated during the manufacturing process can be analyzed through Big Data platforms, enabling the creation of an automated quality management system (AQMS) that assists decision-makers in formulating effective maintenance strategies. In corrective maintenance (CrM), interventions occur only after a mechanical failure, necessitating an inventory of maintenance, repair, and operations (MRO) supplies to prevent production disruptions from defective components. In contrast, preventive maintenance (PvM) employs condition-based, time-based, or interval-based approaches to minimize equipment damage. PvM focuses on process-oriented safety measures, reducing downtime and maintenance costs while enhancing production efficiency.
5.1 Predictive Maintenance in Big Data Framework
Predictive maintenance transforms industrial maintenance by utilizing vast data to foresee equipment failures. This approach aggregates data from sensors, IoT devices, maintenance logs, and operational records, creating a comprehensive view of equipment performance. Advanced analytics, including machine learning and statistical modeling, analyze this data to identify patterns and anomalies indicative of potential failures. By recognizing early signs of equipment issues and correlating them with past maintenance records, predictive maintenance can accurately forecast maintenance needs. Timely alerts enable maintenance teams to act before problems escalate, reducing costly downtime and operational disruptions. This proactive strategy enhances asset reliability, extends equipment life, and optimizes maintenance workflows, ultimately driving significant cost efficiencies and productivity improvements in industrial operations.

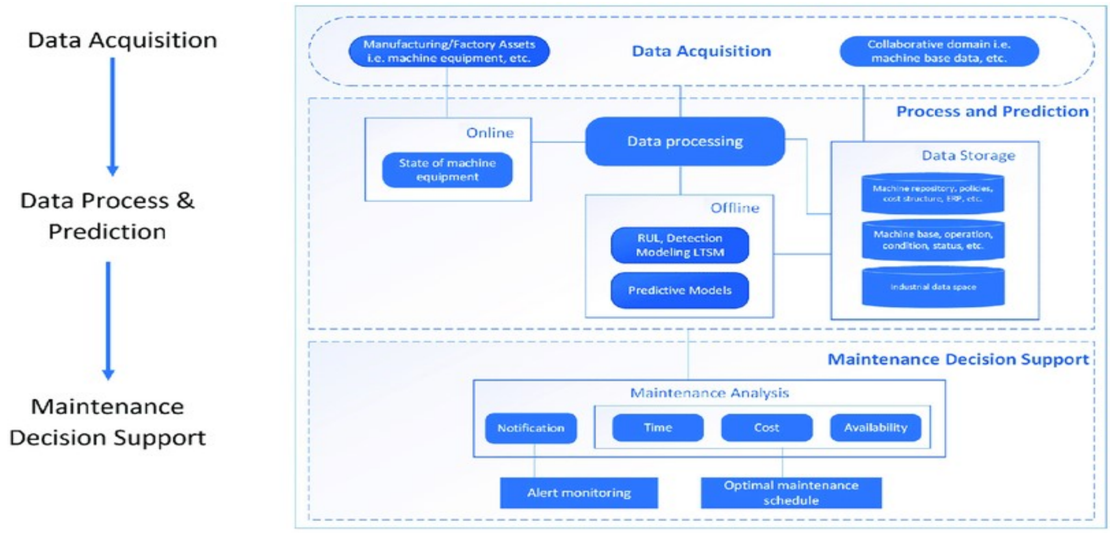

Figure 2. Predictive Maintenance in Big Data Framework

5.2 Maintenance Benefits

The automotive sector stands to gain numerous advantages from an optimized planning process that enhances routine maintenance and boosts overall performance. The primary benefits of predictive maintenance include:

1. Minimized Downtime: Predictive maintenance enables organizations to anticipate maintenance requirements and take proactive measures to address potential issues before they escalate. By identifying and rectifying problems early, businesses can significantly reduce downtime, enhancing vehicle performance and operational productivity.
2. Tailored Maintenance Scheduling: Unlike traditional maintenance approaches that rely on fixed schedules or reactive measures, predictive maintenance offers an accurate scheduling framework based on the real-time condition of each vehicle or component. This allows organizations to synchronize maintenance activities, minimizing unnecessary tasks and maximizing resource utilization.
3. Enhanced Safety: By facilitating the early identification and resolution of safety-related issues, predictive maintenance contributes to improved safety for drivers, passengers, and pedestrians. Proper vehicle maintenance enhances overall safety performance, leading to a reduction in accidents and incidents.
4. Cost Efficiency: By decreasing the frequency of unplanned maintenance and shortening scheduled maintenance windows, predictive maintenance can lead to substantial cost savings. Additionally, it helps organizations minimize spare parts inventory and allocate resources more effectively, further reducing operational expenses.
5. Optimized Asset Performance: Early detection and resolution of potential problems through predictive maintenance enhance the operational uptime of vehicle components and machinery. By ensuring effective maintenance practices, organizations can prolong the lifespan, reliability, and operational availability of their assets.
6. Data-Driven Decision-Making: Utilizing big data analytics to analyze extensive datasets allows organizations to identify patterns, trends, and anomalies. This analytical approach supports informed decision-making regarding maintenance strategies, resource allocation, and operational adjustments, ultimately leading to improved performance outcomes.
7. Increased Customer Satisfaction: By minimizing disruptions and avoiding unplanned maintenance activities, predictive maintenance enhances the customer experience. Consumers value dependable vehicles that require less frequent maintenance, leading to higher satisfaction and loyalty as organizations demonstrate reliability and reduce vehicle downtime.

6. Data Mining Techniques

6.1. Association Rule Mining

1. Apriori Algorithm: This algorithm identifies frequent itemsets within datasets and generates association rules to reveal relationships among various vehicle features and customer preferences. By examining co-occurrences, it aids in understanding customer behavior and feature interactions.
2. FP-Growth Algorithm: Leveraging a frequent pattern growth approach, this algorithm enables efficient discovery of patterns in large datasets. It enhances market basket analysis and facilitates feature bundling by focusing on the most

relevant itemsets without the need for candidate generation.

6.2 .Anomaly Detection

1. Isolation Forest: This method is designed to identify outliers within manufacturing processes, quality control measures, and vehicle performance data. By isolating anomalies, it allows for timely intervention to mitigate potential operational issues.
2. Autoencoders: These deep learning-based models perform unsupervised anomaly detection on sensor data by learning to encode and decode normal operating conditions. Deviations from expected outputs indicate potential anomalies, enabling proactive maintenance measures.

6.3. Text Mining

1. Natural Language Processing (NLP): Implement NLP techniques such as Named Entity Recognition (NER), sentiment analysis, and topic modeling (e.g., LDA, BERT) on unstructured data sourced from customer feedback, service records, and social media. This process extracts actionable insights, helping organizations understand customer sentiment and emerging trends.
2. Keyword Extraction: Employ algorithms like TF-IDF, RAKE, and TextRank to identify significant terms and trends within textual datasets. This information informs product development initiatives and marketing strategies by highlighting consumer interests and needs.

6.4. Dimensionality Reduction

1. Principal Component Analysis (PCA): Utilize PCA to reduce the dimensionality of extensive datasets while maintaining variance. This technique enhances data visualization and analysis efficiency, making complex datasets more interpretable.

2. t-Distributed Stochastic Neighbor Embedding (t-SNE): Apply t-SNE for visualizing high-dimensional data, effectively uncovering hidden patterns and relationships within operational and performance datasets. This method facilitates a better understanding of data structures and clustering tendencies.

7. Future Direction

The landscape of predictive maintenance in the automotive sector is set to experience transformative changes, propelled by cutting-edge technologies and shifting industry dynamics. Here are several pivotal directions for the future:

1. AI and Machine Learning Integration: The automotive industry is anticipated to harness artificial intelligence (AI) and machine learning (ML) algorithms to bolster predictive maintenance functionalities. Sophisticated algorithms will scrutinize extensive datasets from sensors, telematics, and historical maintenance records, enhancing the accuracy of failure predictions and optimizing maintenance schedules.
2. IoT, Connectivity, and Edge Computing: The expansion of Internet of Things (IoT) devices and connected vehicles will facilitate real-time health monitoring of vehicles. Continuous data streams from onboard sensors will feed predictive maintenance systems, enabling proactive issue detection and maintenance optimization. Additionally, edge computing will minimize latency, improve data security, and accelerate response times for critical maintenance alerts.
3. Predictive Analytics Platforms: Automotive manufacturers will invest in powerful predictive analytics platforms designed to efficiently process and analyze large volumes of data. These platforms will unify data from multiple sources, apply advanced analytical methods, and deliver actionable insights to guide predictive maintenance decisions.
4. Digital Twins: The adoption of digital twin technology will allow automotive companies to create virtual representations of vehicles or components. These digital twins will support predictive maintenance by simulating real-world conditions, forecasting performance degradation, and refining maintenance strategies through virtual experimentation.
5. Blockchain for Enhanced Data Security: The integration of blockchain technology will improve data security and integrity within predictive maintenance frameworks. By offering a decentralized and tamper-proof data storage solution, blockchain will ensure the authenticity and reliability of maintenance data, fostering trust among all stakeholders involved.
6. Collaborative Ecosystem Development: Collaboration among automotive OEMs, suppliers, and service providers will lead to the establishment of holistic predictive maintenance ecosystems. These ecosystems will include data-sharing agreements, standardized protocols, and interoperable systems, promoting seamless integration of predictive maintenance solutions throughout the automotive supply chain.
7. Human-Machine Synergy: Although automation and AI-driven algorithms will be pivotal in predictive maintenance, human expertise will remain crucial. Future predictive maintenance systems will facilitate effective collaboration between human operators and intelligent systems, leveraging human insights and domain expertise to enhance predictive models

and refine maintenance strategies.

8. Conclusion

The integration of predictive maintenance within a big data framework in the automotive sector signifies a major evolution towards proactive maintenance methodologies. By leveraging big data analytics, automotive manufacturers can foresee potential equipment failures, implement maintenance schedules in advance, and enhance overall operational efficiency. Historical maintenance records provide critical insights for recognizing patterns and trends, allowing predictive models to accurately forecast maintenance requirements. This proactive strategy not only minimizes downtime and lowers maintenance expenses but also improves asset reliability, delivering substantial advantages to automotive producers. By effectively utilizing big data and cutting-edge analytical technologies, automotive companies can proactively address equipment issues, boost customer satisfaction, and secure a competitive edge in the market.

References

1. Sang, G. M., Xu, L., & de Vrieze, P. (2021). A predictive maintenance model for flexible manufacturing in the context of industry 4.0. *Frontiers in big Data*, *4*, 663466.
2. Alam, M. N., Singh, V., Kaur, M. R., & Kabir, M. S. (2023). Big Data: An overview with Legal Aspects and Future Prospects. Journal of Emerging Technologies and Innovative Research, 10(5), 476-485.
3. Exton, T., & Labib, A. (2002). Spare parts decision analysis–The missing link in CMMSs (Part II). Journal of Maintenance & Asset Management, 17(1), 14–21.
4. Faiz, R., & Edirisinghe, E. A. (2009). Decision making for predictive maintenance in asset information management. Interdisciplinary Journal of Information, Knowledge, and Management, 4, 23–36.
5. Fu, C., Ye, L., Liu, Y., Yu, R., Iung, B., Cheng, Y., & Zeng, Y. (2004). Predictive maintenance in intelligent-control-maintenance-management system for hydroelectric generating unit. Energy Conversion. IEEE Transactions on, 19(1), 179–186.
6. Garcia, M. C., Sanz-Bobi, M. A., & del Pico, J. (2006). SIMAP: Intelligent System for Predictive Maintenance: Application to the health condition monitoring of a windturbine gearbox. Computers in Industry, 57(6), 552–568. doi:10.1016/j. compind.2006.02.011
7. Jardine, A. K., & Tsang, A. H. (2013). Maintenance, replacement, and reliability: theory and applications. CRC Press.
8. Kaiser, K. A., &Gebraeel, N. Z. (2009). Predictive maintenance management using sensor-based degradation models. Systems, Man and Cybernetics, Part A: Systems and Humans. IEEE Transactions on, 39(4), 840–849.
9. Klutke, G.-A., Kiessler, P. C., & Wortman, M. (2003). A critical look at the bathtub curve. IEEE Transactions on Reliability, 52(1), 125–129. doi:10.1109/ TR.2002.804492
10. Lee, J., Ardakani, H. D., Yang, S., & Bagheri, B. (2015). Industrial big data analytics and cyber-physical systems for future maintenance & service innovation. Procedia CIRP, 38, 3–7. doi:10.1016/j.procir.2015.08.026
11. Lee, J., Kao, H.-A., & Yang, S. (2014). Service innovation and smart analytics for industry 4.0 and big data environment. Procedia CIRP, 16, 3–8. doi:10.1016/j. procir.2014.02.001
12. Li, L., Bagheri, S., Goote, H., Hasan, A., & Hazard, G. (2013). Risk adjustment of patient expenditures: A big data analytics approach. Paper presented at the Big Data, 2013 IEEE International Conference on. doi:10.1109/BigData.2013.6691790
13. S. Singh and G. Jagdev, "Execution of Big Data Analytics in Automotive Industry using Hortonworks Sandbox," 2020 Indo – Taiwan 2nd International Conference on Computing, Analytics and Networks (Indo-Taiwan ICAN), Rajpura, India, 2020, pp. 158-163, doi: 10.1109/Indo-TaiwanICAN48429.2020.9181314.
14. Singh, S., Jagdev, G. Execution of Structured and Unstructured Mining in Automotive Industry Using Hortonworks Sandbox. SN COMPUT. SCI. 2, 298 (2021).
15. Brar, T. P. S. (2021). Digital Marketing Performance: Understanding the Challenges and Measuring the Outcomes. In Big Data Analytics for Improved Accuracy, Efficiency, and Decision Making in Digital Marketing (pp. 51-63). IGI Global.
16. Mehta, S., Kukreja, V., Bhattacherjee, A., & Brar, T. P. S. (2023, April). Predicting Rice Leaf Disease Outbreaks using CNN-SVM Models: A Machine Learning Approach. In 2023 IEEE International Conference on Contemporary Computing and Communications (InC4) (Vol. 1, pp. 1-5). IEEE.

17. Banerjee, D., Kukreja, V., Gupta, A., Singh, V., & Brar, T. P. S. (2023, August). CNN and SVM-based Model for Effective Watermelon Disease Classification. In 2023 3rd Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-6). IEEE.
18. Sharma, R. K., Brar, T. P. S., & Gandhi, P. (2021). Defense and Isolation in the Internet of Things. Internet of Things in Business Transformation: Developing an Engineering and Business Strategy for Industry 5.0, 141-168.
19. Brar, T. P. S. (2018). Business intelligence in banking: a study of bi technology implementation and challenges. CGC International Journal of Contemporary Technology
20. Kabir, M. S., & Alam, M. N. (2023). IoT, Big Data and AI Applications in the Law Enforcement and Legal System: A Review. International Research Journal of Engineering and Technology (IRJET), 10(05), 1777-1789.
21. Singh, S., Alam, M. N., Singh, V., & Kaur, S. (2023). Harnessing Big Data Analytics for Optimal Car Choices.
22. Sucharita Debnath, Vivek Sharma, & Sukhpreet Singh. (2024). The Role Of Machine Learning In Social Media Marketing For Business Growth. Educational Administration: Theory and Practice, 30(6), 2747–2750.
23. Singh, S., & Sethi, A. (2024). Analysing And Harnessing Supremacy of Big Data Analytics in Automobile Sector. Journal of Applied Optics, 45, 113-120.
24. Singh, A., Singh, S., Alam, M. N., & Singh, G. Deep Learning for Anomaly Detection in IoT Systems: Techniques, Applications, and Future Directions.
25. Singh, S., Kaur, B., & Kaur, K. (2024). Big Data Using Machine Learning and Deep Learning. Journal of Applied Optics, 45, 97-104.
26. Banerjee, D., Kukreja, V., Gupta, A., Singh, V., & Brar, T. P. S. (2023, August). CNN and SVM-based Model for Effective Watermelon Disease Classification. In 2023 3rd Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-6). IEEE.
27. Brar, T. P. S. (2021). Digital marketing performance: Understanding the challenges and measuring the outcomes. In Big Data Analytics for Improved Accuracy, Efficiency, and Decision Making in Digital Marketing (pp. 51-63). IGI Global.