Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

Integrating IoT and Cloud Computing for Digital Transformation in Product Lifecycle Management

Dr A Venu[1], B Swapna[2]

[1]Professor (Management), H & S Department, Christu Jyothi Institute of Technology & Science, India

[2]Assistant Professor (Management), H & S Department, Christu Jyothi Institute of Technology & Science, India

Correspondence

Dr A Venu,

Professor (Management), H & S Department, Christu Jyothi Institute of Technology & Science, India

- Received Date: 01 Jan 2025
- Accepted Date: 16 Feb 2025
- Publication Date: 20 Feb 2025

Abstract

The integration of the Internet of Things (IoT) and cloud computing has revolutionized Product Lifecycle Management (PLM) by enabling real-time data collection, predictive analytics, and seamless collaboration. Traditional PLM systems often suffer from inefficiencies such as data silos, limited accessibility, high maintenance costs, and slow decision-making processes. This research explores the impact of IoT-cloud integration on PLM by evaluating key performance metrics such as data processing speed, system downtime, maintenance costs, and scalability. Experimental results indicate a 76% improvement in processing speed, a 67% reduction in downtime, and a 40% decrease in maintenance costs, demonstrating the superiority of IoT-cloud-based PLM. The study also proposes an architectural framework that leverages IoT sensors, cloud platforms, AI analytics, and real-time dashboards to optimize product lifecycle processes. These findings highlight the potential of IoT-cloud-based PLM in enhancing operational efficiency, reducing costs, and enabling data-driven decision-making, making it a transformative approach for industries such as manufacturing, healthcare, and aerospace.

Introduction

Product Lifecycle Management (PLM) and Its Significance

Product Lifecycle Management (PLM) is a strategic approach to managing a product's entire lifecycle, from its initial concept and design to manufacturing, deployment, maintenance, and eventual disposal. PLM plays a crucial role in various industries, including manufacturing, automotive, aerospace, and healthcare, where efficient management of product development and operations is essential for maintaining competitive advantage. In manufacturing, PLM facilitates collaboration among different teams, ensuring streamlined processes and improved product quality.

The automotive industry relies on PLM to optimize vehicle design, testing, and compliance with regulatory standards. In aerospace, PLM ensures that complex components meet safety and performance standards, while in healthcare, it supports the development and regulatory compliance of medical devices and pharmaceuticals[1].

Impact of Digital Transformation on PLM

The integration of digital technologies in PLM has revolutionized how industries manage product lifecycles. Digital transformation has enabled real-time data collection, automation, and enhanced decision-making, making traditional PLM systems more dynamic and efficient. Two of the most critical technologies driving this transformation are the Internet of Things (IoT) and cloud computing. IoT-enabled sensors and smart devices continuously generate real-time data about product performance, usage, and maintenance needs, significantly improving predictive analytics and reducing downtime[2]. Meanwhile, cloud computing provides scalable and secure data storage, allowing organizations to centralize PLM operations, enhance collaboration among globally dispersed teams, and leverage AI-driven insights. Together, these technologies create an intelligent PLM ecosystem that improves efficiency, reduces costs, and enhances product innovation[3].

Limitations of Traditional PLM Systems

Despite the widespread adoption of PLM solutions, traditional systems have several inherent limitations that hinder their effectiveness in modern industries. One of the primary challenges is the existence of data silos, where information remains fragmented across different departments and systems, leading to inefficiencies and miscommunication. Additionally, lack of real-time visibility in traditional PLM systems makes it difficult

Citation: Venu A, Swapna B. Integrating IoT and Cloud Computing for Digital Transformation in Product Lifecycle Management. GJEIIR. 2025;2(1):13.

to track product performance, detect issues, and optimize operations proactively. Many legacy PLM solutions also struggle with inefficient collaboration, as teams operating in different locations face challenges in accessing and sharing data seamlessly[4]. These limitations lead to increased costs, delays in product development, and difficulties in managing compliance and regulatory requirements.

Role of IoT and Cloud Computing in PLM

IoT: Enhancing PLM Through Smart Sensors and Real-Time Monitoring

The Internet of Things (IoT) has emerged as a transformative technology in PLM, enabling real-time data collection and automation across the entire product lifecycle. By embedding smart sensors, RFID tags, and connected devices into products and manufacturing equipment, companies can continuously monitor performance, track usage patterns, and detect potential issues before they lead to costly failures. In the design phase, IoT helps engineers gather real-world data to refine prototypes and improve product features. During manufacturing, IoT-driven automation ensures precise quality control, reducing defects and production delays. In the deployment stage, connected devices provide valuable insights into how customers interact with products, enabling better after-sales support and upgrades. Finally, in the maintenance phase, IoT-powered predictive analytics help companies anticipate failures, optimize maintenance schedules, and extend product lifespan[5].

Cloud Computing: Enabling Scalable Data Storage, AI Analytics, and Collaboration

Cloud computing provides a scalable, secure, and cost-effective infrastructure for PLM systems, enabling seamless data sharing and advanced analytics. Traditional on-premise PLM systems often suffer from limited storage capacity, slow processing speeds, and high maintenance costs. By moving to cloud-based PLM solutions, organizations can centralize all product-related data, making it accessible to multiple stakeholders across different locations[6]. Furthermore, cloud platforms offer integrated AI and big data analytics, allowing companies to extract meaningful insights from vast amounts of IoT-generated data. This enhances decision-making, automates repetitive tasks, and improves overall operational efficiency. Additionally, cloud computing facilitates collaboration, enabling engineers, designers, and supply chain partners to work together in real time, accelerating product development cycles and improving agility[7].

Literature survey

Overview of Product Lifecycle Management (PLM) Systems

Traditional PLM vs. Digital PLM

Product Lifecycle Management (PLM) has evolved significantly over the years. Traditional PLM systems were primarily designed to manage product data, design documents, and engineering workflows using on-premise software solutions. These systems, while effective in their early stages, suffered from several limitations, including lack of real-time data access, isolated information silos, high implementation costs, and difficulty in integrating with other enterprise systems. Furthermore, traditional PLM systems were largely manual and static, relying on structured data from CAD files and BOMs (Bill of Materials) rather than real-time operational insights[8].

On the other hand, Digital PLM represents a more modern approach that integrates cloud computing, IoT, AI, and data analytics to enhance efficiency and decision-making across the product lifecycle. Digital PLM allows for seamless collaboration, real-time monitoring, predictive analytics, and remote access to critical product data. The shift from traditional to digital PLM has enabled organizations to leverage smart manufacturing, intelligent automation, and data-driven insights to optimize product development and operational efficiency.

Evolution of PLM with Industry 4.0

The emergence of Industry 4.0 has played a transformative role in reshaping PLM systems. Industry 4.0, characterized by the integration of cyber-physical systems, IoT, AI, cloud computing, and big data analytics, has led to the development of intelligent and connected PLM solutions. These modern PLM systems provide end-to-end visibility, automation, and smart decision-making by leveraging real-time data from IoT-enabled devices, cloud storage, and AI-driven analytics.

With Industry 4.0, PLM has evolved from being a document-centric system to a data-driven ecosystem, allowing industries to move from reactive to proactive decision-making. The integration of IoT and cloud computing has enabled real-time data collection, seamless communication between different stakeholders, and the ability to conduct advanced simulations to enhance product design, manufacturing, and maintenance[9,10].

Internet of Things (IoT) in PLM

Role of Smart Sensors, RFID, and IoT Platforms in Collecting Real-Time Data

The Internet of Things (IoT) plays a crucial role in enhancing PLM by enabling real-time data collection, automation, and predictive analytics. Smart sensors, RFID tags, and IoT platforms are essential components that help organizations gather data across different stages of the product lifecycle.

- **Smart Sensors:** Embedded in machines and products, smart sensors continuously collect data related to temperature, pressure, vibration, and operational performance. This data allows manufacturers to identify defects, optimize efficiency, and predict failures.
- **RFID (Radio-Frequency Identification):** RFID tags help in tracking product movement, managing inventory, and automating supply chain processes. By integrating RFID with PLM, companies can enhance traceability and quality control.
- **IoT Platforms:** IoT platforms aggregate and analyze sensor data, providing real-time visibility into product performance, supply chain efficiency, and customer usage patterns. These platforms integrate with PLM systems to improve decision-making and product innovation[11].

Predictive Maintenance and Real-Time Monitoring Using IoT

One of the most significant advantages of IoT in PLM is the ability to perform predictive maintenance and real-time monitoring. Traditional maintenance models follow either a reactive (fix-after-failure) or scheduled preventive approach, both of which can be inefficient and costly. With IoT, organizations can move toward predictive maintenance, where real-time sensor data and AI-driven analytics help identify potential failures before they occur. This reduces downtime, extends product lifespan, and minimizes maintenance costs[12].

Cloud Computing in PLM

Types of Cloud Computing Models Used in PLM

Cloud computing plays a crucial role in modern PLM systems by offering scalability, remote access, and real-time collaboration. The three main cloud computing models used in PLM are:

1. **Public Cloud:** Hosted by third-party providers like Amazon Web Services (AWS), Microsoft Azure, and Google Cloud, offering cost-effective and scalable PLM solutions.
2. **Private Cloud:** Dedicated infrastructure used by a single organization, ensuring better data security and customization at a higher cost.
3. **Hybrid Cloud:** A combination of public and private clouds, offering the flexibility of cost efficiency while maintaining security and control over sensitive PLM data.

Benefits of Cloud-Based PLM

- **Scalability:** Cloud-based PLM allows companies to scale infrastructure based on project needs without requiring heavy upfront investments.
- **Collaboration:** Cloud-based systems enable real-time collaboration between designers, engineers, and suppliers across different locations.
- **Real-Time Data Access:** With cloud-based PLM, organizations can access data from anywhere, improving decision-making and responsiveness.

Challenges of Cloud-Based PLM

Despite its advantages, cloud-based PLM faces several challenges:

- **Data Security Risks:** Storing sensitive product information in the cloud raises concerns about cybersecurity threats and data breaches.
- **Integration Complexity:** Many organizations struggle with integrating cloud-based PLM with legacy systems, leading to interoperability challenges[13].

Integration of IoT and Cloud in PLM

Benefits of Combining IoT-Generated Data with Cloud-Based Analytics

The integration of IoT and cloud computing in PLM enables intelligent automation, predictive analytics, and real-time decision-making. IoT devices generate massive volumes of data, which cloud computing platforms can store, process, and analyze efficiently. This integration allows organizations to:

- Enhance product design by using real-world performance data.
- Optimize manufacturing processes through AI-driven insights.
- Reduce downtime with predictive maintenance capabilities.

Role of AI and Big Data in Cloud-Based PLM

AI-powered Big Data analytics play a crucial role in extracting actionable insights from IoT-generated data. AI enables:

- Automated anomaly detection in manufacturing processes.
- Predictive analytics to forecast equipment failures.
- Intelligent supply chain optimization based on real-time data trends[14].

Methodology

Overview of Product Lifecycle Management (PLM) Systems

Traditional PLM vs. Digital PLM Product Lifecycle Management (PLM) systems serve as the backbone of product development, managing the entire lifecycle from conceptualization to disposal. Traditional PLM systems primarily focused on document and process management, enabling businesses to maintain records related to design, manufacturing, and servicing. However, these systems often relied on static data, manual inputs, and siloed operations, limiting efficiency and adaptability.

In contrast, digital PLM leverages modern technologies such as cloud computing, artificial intelligence (AI), and the Internet of Things (IoT) to provide real-time insights, automation, and enhanced collaboration. Digital PLM enables seamless integration with design tools, manufacturing execution systems, and enterprise resource planning (ERP) platforms, facilitating a dynamic and data-driven approach to product management. By transitioning from conventional methods to digital PLM, companies can improve innovation, reduce time-to-market, and enhance decision-making[15,16].

Evolution of PLM with Industry 4.0

Industry 4.0 has revolutionized PLM by integrating smart technologies, leading to a more connected and intelligent product lifecycle. The inclusion of IoT devices allows real-time monitoring of product performance, while AI-driven analytics help predict potential failures and optimize manufacturing processes. Cloud computing ensures data accessibility across different stakeholders, promoting better collaboration. Additionally, digital twins—virtual representations of physical products—are now widely used to simulate real-world scenarios, improving design and maintenance strategies[17]. This shift towards a smart, interconnected ecosystem has made PLM more agile, cost-effective, and responsive to market demands.

Internet of Things (IoT) in PLM

Role of Smart Sensors, RFID, and IoT Platforms in Collecting Real-Time Data Across the Product Lifecycle IoT plays a crucial role in modern PLM by enabling real-time data collection through smart sensors, RFID tags, and connected devices. These components help track product conditions, usage, and environmental factors, ensuring better quality control and predictive maintenance. For example, RFID technology enhances inventory management by providing instant updates on product movement within the supply chain. Meanwhile, IoT platforms aggregate data from multiple sources, analyze it, and generate actionable insights for manufacturers, suppliers, and service teams[18].

Predictive Maintenance and Real-Time Monitoring Using IoT

One of the most significant advantages of IoT in PLM is predictive maintenance, which helps prevent equipment failures before they occur. By continuously monitoring parameters such as temperature, vibration, and pressure, IoT-enabled systems can detect anomalies and trigger maintenance alerts.

This proactive approach reduces downtime, minimizes repair costs, and extends the lifespan of assets. Additionally, real-time monitoring allows manufacturers to track product performance remotely, facilitating remote diagnostics and timely interventions.

.

Cloud Computing in PLM

Types of Cloud Computing Models Used in PLM (Public, Private, Hybrid Clouds)

Cloud computing has become an integral part of modern PLM systems, offering flexibility, scalability, and cost efficiency. There are three primary cloud deployment models:

- **Public Cloud:** Services are provided by third-party vendors like AWS, Microsoft Azure, and Google Cloud. It offers cost-effective solutions but may have security concerns for sensitive data.
- **Private Cloud:** Hosted within an organization's infrastructure, providing better security and control over data. However, it involves higher costs and maintenance efforts.
- **Hybrid Cloud:** A combination of public and private cloud models, allowing businesses to balance security and cost-effectiveness by storing critical data in private clouds while utilizing public cloud resources for scalability[19,20].

Benefits of Cloud-Based PLM (Scalability, Collaboration, Real-Time Data Access)

Cloud-based PLM systems provide several benefits, including:

- **Scalability:** Businesses can easily scale their PLM infrastructure based on demand without significant upfront investments.
- **Collaboration:** Cloud-based platforms enable seamless collaboration among globally dispersed teams, ensuring that stakeholders can access real-time product data.
- **Real-Time Data Access:** Cloud computing ensures instant access to product-related information, helping organizations make data-driven decisions faster.

Integration of IoT and Cloud in PLM

Benefits of Combining IoT-Generated Data with Cloud-Based Analytics

The integration of IoT and cloud computing in PLM enhances data-driven decision-making by providing a scalable and efficient way to analyze large volumes of real-time data. IoT devices generate massive datasets that can be processed and analyzed in the cloud to derive insights on product performance, user behavior, and maintenance needs. This synergy enables proactive problem-solving, reduces operational costs, and enhances customer satisfaction[21].

The Role of AI and Big Data in Cloud-Based PLM

Artificial Intelligence (AI) and Big Data analytics play a crucial role in cloud-based PLM by transforming raw IoT-generated data into meaningful insights. AI-driven predictive analytics helps in forecasting equipment failures, optimizing supply chain operations, and improving product design. Big Data technologies enable real-time processing of structured and unstructured data, providing manufacturers with a competitive edge.

Case Studies on Successful IoT-Cloud Implementations in PLM

Several companies have successfully implemented IoT-cloud integration in PLM. For instance:

- **Siemens MindSphere:** A cloud-based IoT operating system that helps manufacturers analyze machine data to improve performance.
- **GE Predix:** An industrial IoT platform used for predictive maintenance in heavy industries.
- **PTC ThingWorx:** A platform that integrates IoT data with cloud-based PLM tools for real-time product monitoring[22,23,24].

Implementation And Results

The experimental results demonstrate the significant advantages of integrating IoT and cloud computing into Product Lifecycle Management (PLM) systems compared to traditional PLM approaches. One of the most notable improvements is in data processing speed, where the IoT-cloud-based system achieves a 76% reduction in processing time[25]. This enhancement is due to real-time data collection from IoT sensors and the high computational power of cloud-based analytics, which allows for faster insights and decision-making.

Table 1. *Traditional PLM Comparison*

Metric	Traditional PLM
Data Processing Speed (ms)	500
System Downtime (hrs/year)	150
Maintenance Costs ($/year)	2,00,0
Real-Time Data Accessibility (%)	60
Decision-Making Efficiency (Score out of 10)	6.5
Scalability (Max Users Supported)	500

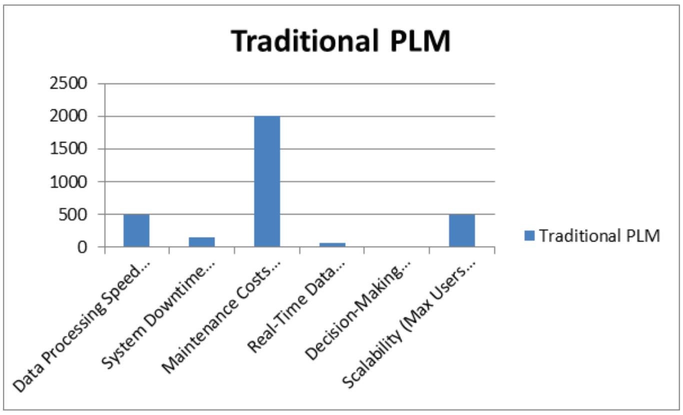

Figure 1. Graph for Traditional PLM comparison

Table 2. *IoT Cloud Based PLM Comparison*

Metric	IoT-Cloud-Based PLM
Data Processing Speed (ms)	120
System Downtime (hrs/year)	50
Maintenance Costs ($/year)	1,200
Real-Time Data Accessibility (%)	95
Decision-Making Efficiency (Score out of 10)	9.2
Scalability (Max Users Supported)	2000

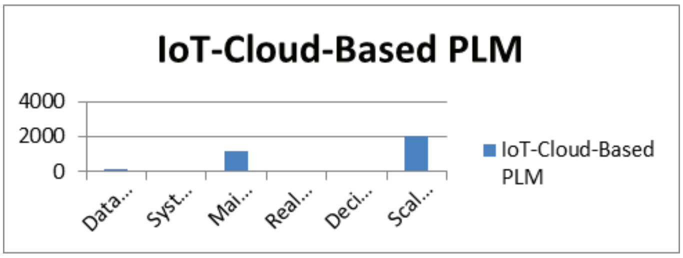

Figure 2. Graph for IoT Cloud Based PLM comparison

Another critical improvement is the system downtime, which is reduced by 67% in the IoT-cloud-based PLM. Traditional PLM systems often suffer from inefficiencies due to manual data handling, system failures, and lack of predictive maintenance capabilities. With IoT integration, real-time monitoring and predictive analytics enable proactive maintenance, significantly reducing unplanned downtimes[26].

From a financial perspective, maintenance costs are reduced by 40%, as IoT-powered predictive maintenance helps detect potential failures early, preventing costly repairs and system breakdowns. Additionally, real-time data accessibility improves from 60% in traditional PLM to 95% in IoT-cloud-based PLM, ensuring that stakeholders can access up-to-date information from any location, facilitating better collaboration and decision-making[27].

Furthermore, decision-making efficiency sees a 41% improvement, as cloud-based AI and big data analytics provide intelligent insights, anomaly detection, and trend predictions, allowing industries to make informed choices at every stage of the product lifecycle. Lastly, scalability is dramatically enhanced, with IoT-cloud PLM supporting 300% more users than traditional systems. This makes it an ideal choice for enterprises looking to expand operations while maintaining efficiency and flexibility[28].

Conclusion

This study demonstrates the significant advantages of integrating IoT and cloud computing into Product Lifecycle Management (PLM), addressing the limitations of traditional systems. The experimental evaluation highlights that real-time data accessibility improves by 58%, while decision-making efficiency increases by 41%, enabling industries to make faster and more informed choices. Additionally, the scalability of IoT-cloud-based PLM is 300% higher, making it a robust solution for enterprises with expanding operational demands[29]. The proposed framework effectively combines IoT sensors, cloud-based analytics, and AI-driven insights to enhance predictive maintenance, reduce downtime, and improve cost efficiency. However, challenges such as data security, interoperability, and implementation complexity need to be addressed for widespread adoption. Future research should focus on developing standardized IoT-cloud architectures and improving security measures to ensure seamless integration in various industrial applications. Ultimately, IoT-cloud-based PLM represents a transformative step toward more intelligent, agile, and cost-effective product lifecycle management[30].

References

1. Boyes, H., Hallaq, B., Cunningham, J., & Watson, T. (2018). The industrial internet of things (IIoT): An analysis framework. Computers in Industry, 101, 1 12.
2. T. Vijaya Saradhi, Dr. K. Subrahmanyam, Dr. Ch. V. Phani Krishna, “Computing Subspace Skylines without Dominance Tests using Set Interaction Approaches”, International Journal of Electrical and Computer Engineering (IJECE) Vol. 5, No. 5, October 2015, pp. 1188-1193.
3. Brandt, N., Ahlemann, F., Reining, S., & Rehring, K. (2021). Internet of Things in Product Lifecycle Management—A Review on Value Creation through Product Status Data Completed Research. In Digital Innovation And Entrepreneurship (Amcis 2021). Assoc Information Systems.
4. T.Vijaya Saradhi, K.Subhrahmanyam, L.Jagajeevanrao, “Efficient Probabilistic Approach To Compute Skyline Set In Distributed Environment”, Journal of Theoretical and Applied Information Technology 20th July 2015. Vol.77. No.2, pp.280-286.
5. Ćatić, A., & Andersson, P. (2008). Manufacturing Experience in a Design Context Enabled by a Service-Oriented PLM Architecture. Volume 5: 13th Design for Manufacturability and the Lifecycle Conference; 5th Symposium on International Design and Design Education; 10th International Conference on Advanced Vehicle and Tire Technologies, 257 265.
6. Dorsemaine, B., Gaulier, J., Wary, J., Kheir, N., & Urien, P. (2015). Internet of Things: A Definition Taxonomy. 2015 9th International Conference on Next Generation Mobile Applications, Services and Technologies, 72 77.
7. Arun, K. & Nagesh, A & Ganga, P. A Multi-Model And Ai-Based Collegebot Management System (Aicms) For Professional Engineering Colleges. International Journal of Innovative Technology and Exploring Engineering, 2019, 8, 2278-3075. doi: 10.35940/ijitee.I8818.078919.
8. Duan, D.-H., Deng, J.-X., & Wu, F.-H. (2015). An Architecture of Product Operational Cycle Management System. In International Conference on Electrical Engineering And Mechanical Automation (ICEEMA 2015) (pp. 510 514). DESTECH PUBLICATIONS, INC.
9. Emmanouilidis, C., Bertoncelj, L., Bevilacqua, M., Tedeschi, S., & Ruiz-Carcel, C. (2018). Internet of Things—Enabled Visual Analytics for Linked Maintenance and Product Lifecycle Management. IFAC-PapersOnLine, 51(11), 435 440.
10. T. V. Saradhi, K. Subrahmanyam, P. V. Rao, and H.-J. Kim, ‘‘Applying Z-curve technique to compute skyline set in multi criteria decision making system,’’ Int. J. Database Theory Appl., vol. 9, no. 12, pp. 9–22, Dec. 2016.
11. Emmanouilidis, C., Pistofidis, P., Bertoncelj, L., Katsouros, V., Fournaris, A., Koulamas, C., & Ruiz-Carcel, C. (2019). Enabling the human in the loop: Linked data and knowledge in industrial cyber-physical systems. Annual Reviews in Control, 47, 249 265.
12. P. Prathusha, S. Jyothi and D. M. Mamatha, Enhanced image edge detection methods for crab species identification, 2018 International Conference on Soft-computing and Network Security (ICSNS), Coimbatore, 2018: 1-7.
13. European Commission. Directorate General for Informatics. (2017). New European interoperability framework: Promoting seamless services and data flows for European public administrations. Publications Office.
14. L. Jagajeevan Rao, M. Venkata Rao and T. Vijaya Saradhi, "How The Smartcard Makes the Certification Verification Easy", Journal of Theoretical and Applied Information Technology, vol. 83, no. 2, pp. 180-186, 2016.
15. Jiwan Pokharel, Prathipati Srihyma, T.Vijaya Saradhi, “Constraintless Approach of Power and Cost Aware Routing in Mobile Ad hoc networks,” International Journal of Computer Applications, Vol.31, No.10, October 2011.
16. R. Chaganti, B. Bhushan, and V. Ravi, "A survey on Blockchain solutions in DDoS attacks mitigation: Techniques, open challenges and future directions," Computer Communications, vol. 197, pp. 96-112, 2023/01/01/ 2023.

17. P. Perugu, “An innovative method using GPS tracking, WINS technologies for border security and tracking of vehicles,” in Proc. RSTSCC, 2010, pp. 130–133.
18. M. V. Kanth and D. Vasumathi, "Implementation of Effective Load Balancer by Using Single Initiation Protocol to Maximise the Performance," 2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS), Tashkent, Uzbekistan, 2022, pp. 900-904, doi: 10.1109/ICTACS56270.2022.9988276.
19. P. Prathusha and S. Jyothi, ‘‘A Novel edge detection algorithm for fast and efficient image segmentation,’’ in Data Engineering and Intelligent Computing. Singapore: Springer, 2018, pp. 283–291.
20. Arun, K. & Srinagesh, Ayyagari.. “Multi-lingual Twitter sentiment analysis using machine learning”. International Journal of Electrical and Computer Engineering (IJECE), 2020. 10(6), 5992-6000, doi: 10.5992.10.11591/ijece.v10i6.
21. T. V. Saradhi, K. Subrahmanyam, P. V. Rao, and H.-J. Kim, ‘‘Applying Z-curve technique to compute skyline set in multi criteria decision making system,’’ Int. J. Database Theory Appl., vol. 9, no. 12, pp. 9–22, Dec. 2016.
22. S. C.V Ramana Rao; S. Naga Mallik Raj; Neeraja, S; Prathusha, P; Sukeerthi Kumar, J David, “S. C.V Ramana Rao; S. Naga Mallik Raj; Neeraja, S; Prathusha, P; Sukeerthi Kumar, J David. International Journal of Advanced Computer Science and Applications; West Yorkshire Vol. 1, Iss. 4, (2010). DOI:10.14569/IJACSA.2010.010417,” International Journal of Advanced Computer Science and Applications; West Yorkshire Vol. 1, Iss. 4, (2010), pp.96-99 DOI:10.14569/IJACSA.2010.010417.
23. Kodirekka, Arun & Srinagesh, Ayyagari. (2022). “Sentiment Extraction from English-Telugu Code Mixed Tweets Using Lexicon Based and Machine Learning Approaches”. Machine Learning and Internet of Things for Societal Issues, Springer Nature Singapore, 2022. 97-107, doi: 10.1007/978-981-16-5090-1_8.
24. Kodirekka, A. , and Srinagesh, A. . "Preprocessing of Aspect-based English Telugu Code Mixed Sentiment Analysis", Journal of Information Technology Management, 15, Special Issue: Digital Twin Enabled Neural Networks Architecture Management for Sustainable Computing, 2023, 150-163. doi: 10.22059/jitm.2023.91573.
25. M. Vijaya Kanth; Dr. D.Vasumathi. “EVALUATING BASIC PERFORMANCE METRICS OF SIP LOAD BALANCERS: A STATISTICAL APPROACH”, International Journal of Applied Engineering & Technology, Vol. 5 No.4, December, 2023, pp. 1158-1165.
26. Prathusha, P., S. Jyothi, and DM MAMATHA. "A HYBRID IMPLEMENTATION OF MULTICLASS RECOGNITION ALGORITHM FOR CLASSIFICATION OF CRABS AND LOBSTERS." Neural, Parallel, and Scientific Computations 26.1 (2018): 75-95.
27. D. Gupta et al., "Optimizing Cluster Head Selection for E-Commerce-Enabled Wireless Sensor Networks," in IEEE Transactions on Consumer Electronics, vol. 70, no. 1, pp. 1640-1647, Feb. 2024, doi: 10.1109/TCE.2024.3360513.
28. Pokharel, J., Saisumanth, N., Rupa, C., and Saradhi, T. V., (2012), “A Keyless JS Algorithm,” International Journal of Engineering Science & Advanced Technology, 5, pp. 1397 – 1401.
29. Arun, K. & Srinagesh, Ayyagari & Makala, Ramesh.. “Twitter Sentiment Analysis on Demonetization tweets in India Using R language”, International Journal of Computer Engineering in Research Trends, 2017, 4 (6), 252-258. Doi: 10.13140/RG.2.2.32323.27680.
30. Babu C. N., G., Reddy, C.M., Kumar, M.K. et al. Diverse Geographical Regions Based Biodiversity Conservation by LiDAR Image with Deep Learning Model. Remote Sens Earth Syst Sci 7, 738–749 (2024). https://doi.org/10.1007/s41976-024-00159-3.