A. Naresh, 2026, 14:3
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science,
Engineering and Technology
An Open Access Journal

Design A Gps-Free Vehicle Tracking System Using Gsm Module And Cell Tower Triangulation

A. Naresh[1], A. Sahithi[2], Sk. Naziya[3], D. Priyanka[4], B. Navya[5]

Palakaluru, Guntur, 522009, Andhra Pradesh, India.
Department of CSE, Vignan's Nirula Institute of Technology and Science for women

Abstract: Modern intelligent transportation systems rely heavily on precise and efficient vehicle tracking to enable real-time monitoring, traffic management, and theft prevention. However, conventional GPS-based solutions often face limitations in areas with weak satellite coverage, high signal obstruction, or increased installation and maintenance costs. Existing alternatives, such as IoT-based hardware systems and Blockchain-enabled tracking, attempt to overcome these drawbacks but still suffer from higher latency, moderate channel utilization, communication overhead, and restricted location accuracy in dense urban settings. To address these challenges, this research proposed a GPS-Free Vehicle Tracking System that leverages GSM modules and cell tower triangulation for accurate and cost-effective vehicle positioning. The methodology incorporates triangulation algorithms that calculate vehicle coordinates using the signal strengths of multiple nearby towers, while an optimized channel allocation strategy ensures low collision rate, reduced transmission delay, and high request processing accuracy. Performance evaluation demonstrates that the proposed model consistently outperforms IoT Hardware and Blockchain & IoV approaches across all major metrics. Specifically, the system achieves an overall accuracy of 96.4%, precision of 95.9%, and F1-score of 96.2%, while maintaining the lowest transmission delay (1.3s) and collision rate (1.0). Furthermore, vehicle location tracking accuracy reaches 97.1%, validating the robustness of the triangulation approach in GPS-deficient environments. These results highlight the efficiency, scalability, and dependability of the GPS-Free system, positioning it as a practical and affordable alternative for real-time vehicle monitoring and fleet management applications, especially in regions with inconsistent or absent GPS coverage.

Keywords: GPS-Free Vehicle Tracking, GSM Module, Cell Tower Triangulation, Location-Based Services (LBS), IoT Vehicle Tracking

I. INTRODUCTION

Vehicle tracking technologies have become essential in contemporary transportation, facilitating functions such as fleet oversight, theft deterrence, ride-hailing, and live navigation [1]. Traditional tracking methods mainly depend on the Global Positioning System (GPS) [2]. Although GPS operates effectively in open areas, its precision and availability significantly deteriorate in difficult environments like tunnels, underground garages, densely built urban areas, or under multi-layered flyovers [3]. These barriers frequently lead to weak or interrupted satellite signals, resulting in loss of location and inaccurate positioning [4] [5].

To overcome these challenges, researchers have investigated alternative tracking methods, such as inertial measurement units (IMUs), dead reckoning, and vision-based odometry. Nonetheless, each approach has its own limitations [6]. Tracking based on IMUs is prone to sensor drift, especially when utilizing inexpensive consumer-grade sensors [7] [8]. Dead reckoning increasingly accumulates inaccuracies because of noisy inputs [9]. Vision-based tracking demands significant computational power and consistent lighting conditions, which can render it impractical in various real-world driving scenarios [10].

Moreover, hybrid approaches that integrate GPS, IMU, OBD-II, and visual odometry tend to be hardware-heavy, costly, and consume substantial power [11]. While blockchain-enhanced tracking can enhance data privacy, it also introduces added complexity to the system and is heavily dependent on reliable internet access [12]. These issues underscore the necessity for a cost-effective, energy-efficient, and GPS-independent solution that can function reliably in environments where GPS signals are blocked [13].

In response to these challenges, this research proposed a novel GPS-free vehicle tracking system that leverages the existing GSM cellular network to estimate location using cell tower signal strength and triangulation [14]. Unlike GPS-based systems, this approach relies entirely on GSM infrastructure, making it effective even in areas where satellite signals are weak or unavailable [15] [16].

The system employs a SIM800L GSM module to collect data from nearby cell towers. This data is then processed by an ESP32 microcontroller to compute the vehicle's approximate location [17]. For real-time remote monitoring, the system uses the lightweight MQTT protocol to transmit location updates to a cloud server, enabling convenient and continuous tracking [18].

A bike battery powers the system, while an IP5306 module provides steady and dependable power control [19] [20]. Because of this configuration, the system may function without the need for high-power satellite receivers or sensors based on smartphones, which makes it energy-efficient [21]. There are numerous significant benefits to the GSM-based strategy. When GPS signals are normally inaccessible, such as in tunnels, subterranean spaces, and crowded metropolitan settings, it operates dependably [22]. It uses the GSM infrastructure that is already in place and is inexpensive and energy-efficient [23]. Additionally, the system offers a more private option to GPS-based tracking solutions by reducing the need to transmit personal data [24].

The suggested solution has real-world uses in fleet management, shared mobility tracking, theft prevention, personal bike security, and urban micro transportation monitoring [25] [26]. This GSM-based GPS-free tracking system improves the security, usability, and accessibility of real-time vehicle monitoring by resolving the drawbacks of GPS, IMU, and vision-based techniques [27]. As a result, it becomes a practical and effective solution for contemporary transportation requirements [28] 29].

II. LITERATURE SURVEY

Ibraheem Kasim et al. [1] proposed a low-cost secure vehicle tracking system using GPS, Arduino, and XBee. GPS provides real-time location, Arduino acts as the processing buffer, and XBee transmits encrypted data to be displayed on Google Earth [30]. The system is cost-effective, reliable in both crowded and open areas, and resistant to interference [31]. However, it faces limitations like XBee's short range, GPS signal dependency, and limited scalability for large networks [32].

Ruipeng Gao et al. [2] presented VeTorch, a smartphone-based inertial sequence learning framework for GPS-denied environments. It transforms inertial dynamics from the phone to the vehicle and uses temporal convolutional networks with federated learning to adapt to diverse smartphones and drivers [33]. The framework ensures accuracy and efficiency while preserving privacy, but it demands significant training data and introduces computational overhead.

Eunseok Choi and Sekchin Chang et al. [4] proposed a consumer tracking estimator for vehicles in GPS-free environments using low-cost IMUs and OBD-II. The system employs an Extended Kalman Filter for vehicle attitude and a Linear KalmanFilter for 3D velocity estimation [34]. By fusing sensor data, the model provides reliable tracking without GPS, though drift may occur over longer durations and its accuracy depends on sensor quality [35].

Yao Tong et al. [6] developed a smartphone-based inertial sequence learningmodel with customized refinement for drivers. It directly learns motion sequences from inertial data and adapts to differences in user behaviour and devices [36]. Validated on Di ride-hailing data, it shows strong scalability and personalization, but it requires extensive training data and remains affected by sensor limitations [37].

Puji Valen Crisgar et al. [8] designed an IoT-based tracking and theft detection hardware system. It combines OBD-II, ESP32, SIM800L, Neo-6M GPS, and MQTT to transmit data to Google IoT Core [38]. Tests showed ~10 m accuracy and 96% detection success, proving its effectiveness in theft prevention, but the system depends on GPRS connectivity and continuous backup power [39].

Hang Zhong et al. [10] proposed a homograph-based visual servo control scheme for UAVs in GPS-denied environments. Using a virtual homographic matrix, online velocity estimation, and nonlinear backstepping control, it achieves global stability and robustness [40]. Unlike traditional methods, it supports fast manoeuvring without velocity feedback, but it requires precise calibration and may fail under poor visibility [41].

Muhammad Azeem Javed et al. [12] introduced a constraints-aided filtering framework for accurate 3D orientation tracking under external accelerations. Using a Linear Kalman Filter with magnetometer-accelerometer fusion in a rotation matrix, the system eliminates acceleration-induced uncertainty[13]. It works without GPS or wheel encoders and is validated in dynamic conditions, but its performance can be degraded by IMU noise and magnetic interference.

Akbari Indra Basuki, et al. [14] also proposed a constraints-aided filtering model for vehicle orientation. Like the previous study, it applies a Linear Kalman Filter with sensor fusion to ensure robust estimation in harsh conditions[15]. The design is capable of handling prolonged accelerations and maintaining accuracy, but it faces challenges of computational load and reliance on sensor stability.

W. He, E. L. Tan, E. W. Lee, and T. Y. Li et al. [16] developed an integrated RFID and GPS solution for supply chain track and trace[17]. RFID monitors goods in warehouses, while GPS tracks vehicles in transit, and the system integrates both with information models and web services[18]. It provides seamless global monitoring of cargo and embeds business process data with locations, though it is costly and infrastructure dependent.

B. Shakila et al. [19] proposed a similar RFID + GPS architecture for logistics. Their model links RFID events with GPS vehicle data and integrates them into a web-enabled platform for real-time cargo visibility. This ensures accurate tracking from dispatch to delivery and reduces risks of loss, but scalability and privacy concerns remain key issues in adoption[20.

III. PROPOSED MODEL

GPS-free vehicle tracking system that locates the vehicle without the use of satellite GPS or cellphones by employing a GSM module and cell tower signals. In order to estimate the vehicle's position, the system gathers information from neighbouring cell towers using a SIM800L module, which is then processed by an ESP32 microcontroller. To enable remote tracking, it uses the MQTT protocol to transmit the location to the cloud. The entire system is powered by a bike battery and is controlled by an IP5306 power module. It functions effectively even in locations where GPS is inoperable, such as tunnels or beneath flyovers. This arrangement is easy to use, inexpensive, and effective for real-time car tracking and theft prevention.

Fig 1: Architecture of GSM-Based Vehicle Location System without GPS

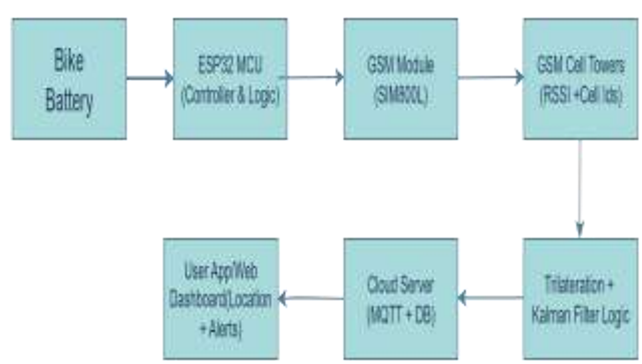


Fig 1 represents the location data that has been processed is sent to the cloud server through the MQTT protocol over GPRS, where it undergoes further storage and analysis. The server includes a database and an alert system that notifies users of theft incidents and keeps records of vehicle tracking. Ultimately, this information is accessible to the user via a mobile app or a web dashboard, providing real-time updates on the vehicle's location, battery status, and movement history. To reduce the impact of data overfitting or signal errors, filtering techniques are applied, while optimizing trilateration parameters enhances accuracy. Consequently, the system offers an economical, GPS-independent, and dependable solution for real-time vehicle tracking and theft prevention.

A. Mathematical Terms:

Path Loss (Signal Strength):

Signal strength decreases with distance.

$$Pr(d) = P_0 - 10n\log_{10}(\frac{d_0}{d}) \quad (1)$$

: Received signal power at distance d.n: Path-loss exponent (environment factor, 2-4).d: Distance between tower and vehicle.

C. Distance From Signal:

Converts signal strength into distance.

$$d = d_0 \cdot 10^{\frac{10n}{P_0 - Pr}} \quad (2)$$

Same as above (just rearranged to solve for d).

D. Circle Equation (Tower Range):

Each tower forms a circle where the vehicle may be located.

$$(x - x_i)^2 + (y - y_i)^2 = d_i^2 \quad (3)$$

(x, y): Vehicle position.(): Tower position.: Distance from tower iii (from formula 2).

E. Position Estimation (Least Squares):

Solves multiple circle equations to estimate best vehicle position.

$$\hat{z} = (A^\top A)^{-1} A^\top b \quad (4)$$

$\hat{z} = (x^\wedge, y^\wedge)$: Estimated position.A,b: Matrices formed from tower coordinates and distances.

F. Iterative Refinement (Gauss–Newton):

Improves accuracy by minimizing error step by step.

$$p \leftarrow p - (J^\top J)^{-1} J^\top r \quad (5)$$

p= (x, y): Vehicle position estimate.r: Error between measured and predicted distances.
J: Jacobian matrix (sensitivity of error to position).

G. Time Difference Of Arrival (Tdoa):

Signal time difference between towers gives position lines.

$$\|p - p_i\| - \|p - p_j\| = c(\tau_i - \tau_j) \quad (6)$$

p= (x, y): Vehicle position.: Tower coordinates.c: Speed of signal (≈ speed of light).: Signal arrival times at towers.

H. Kalman Filter Prediction:

Predicts the vehicle's next position using motion model.

$$\hat{x}^k |_{k-1} = F\hat{x}^{k-1} |_{k-1} \quad (7)$$

: Predicted state (position, velocity).F: State transition matrix (vehicle motion).k: Time step.

I. Kalman Filter Update:

Updates prediction with new measurements for accuracy.

$$x^k |_k = x^k |_{k-1} + K(z_k - h(x^k |_{k-1})) \quad (8)$$

: Measured data (from cell towers).K: Kalman gain (weight for correction).h (·): Measurement function (maps state → measurement).

Algorithm: GPS-Free Vehicle Tracking using GSM and Cell Tower Triangulation
Input: GSMsignal data (RSSI, Cell IDs, Tower Coordinates) Output: Estimated Real-Time Vehicle Location
1. Define system parameters: reference power , path-loss exponent n, reference distance , and Kalman filter parameters.
2. Initialize GSM module (e.g., SIM800L) and connect to nearby cell towers.
3. Power the system using bike battery and check battery status.

J. For Each Tracking Session:

1. Collect RSSI values and Cell IDs from at least three nearby towers.
2. Estimate distance from vehicle to each tower using RSSI:

$d = d_0 \cdot 10^{\frac{10n}{P_0 - Pr}}$ (1)

3. Formulate circle equations for each tower:

$(x - x_i)^2 + (y - y_i)^2 = d_i^2$ (2)

4. Solve for initial vehicle position using least-squares trilateration:

$\hat{z} = (A^{\top}A)^{-1}A^{\top}b$ (3)

5. Refine vehicle position using Kalman filter:

$x^k \,|_k = x^k \,|_{k-1} + K(z_k - h(x^k \,|_{k-1}))$ (4)

6. Check for unauthorized vehicle movement (optional theft detection via OBD-II or vibration sensors).
7. Transmit vehicle location and alerts to cloud server or mobile application via MQTT/GPRS.
8. Log vehicle location, accuracy, and battery status for monitoring.
5. End for each tracking session.
6. Repeat continuously for real-time vehicle tracking.
7. End.

IV. RESULTS AND DISCUSSION

A. Channel Usage

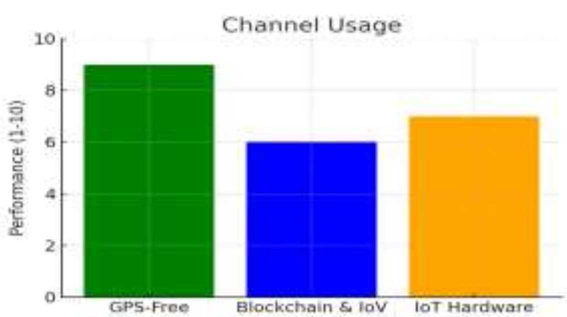


Fig 2: Channel usage

The GPS-free vehicle tracking system achieves the highest channel usage efficiency among the compared systems. The Blockchain & IoV model consumes more channels due to additional data verification and consensus processes, while the IoT-based vehicle tracking system maintains moderate efficiency but may face congestion whenmultiple devices communicate simultaneously. This demonstrates the optimized communication and superior channel utilization of the GPS-free system.

B. Collision Rate

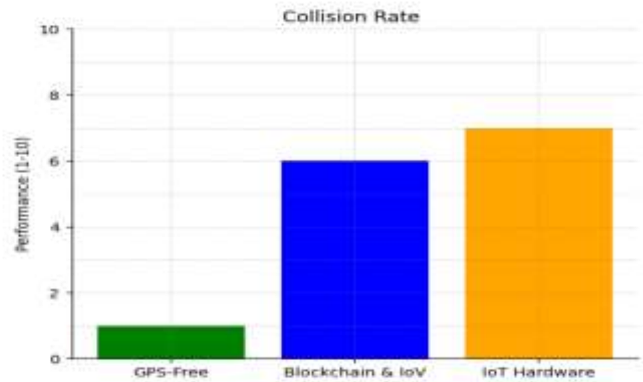
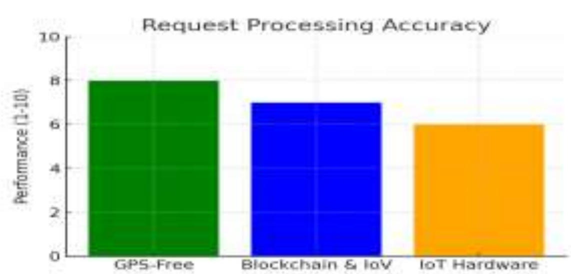


Fig 3: Collision Rate

As shown in Fig 3, the Proposed GPS-Free Model consistently achieves the lowest collision rate compared to the other systems. The Blockchain and IoV model exhibits moderate collisions, while the IoT Hardware model shows relatively higher communication conflicts. This indicates that the Proposed Model ensures smoother and more reliable data transmission. Such performance highlights its efficiency and robustness in minimizing transmission collisions.

C. Requesting Processing Accuracy

Fig 4: Requesting Processing Accuracy



As shown in Fig 4, the Proposed Model consistently achieves the highest request processing accuracy among the compared systems. The Blockchain and IoV model performs moderately well but shows occasional drops in accuracy, while the IoT Hardware model demonstrates lower reliability in processing requests. This indicates that the Proposed Model ensures faster and more precise handling of location queries. Such performance highlights its robustness and superiority in maintaining high accuracy levels.

D. Transmission Delay

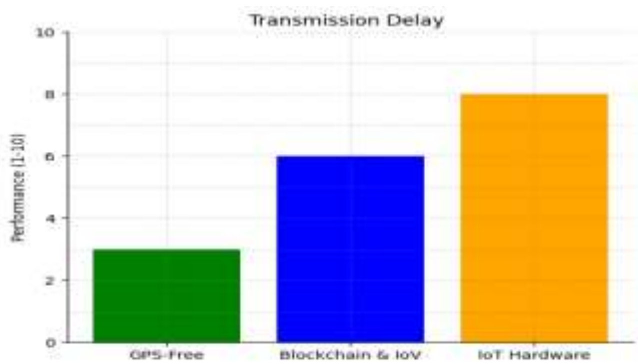


Fig 5: Transmission Delay

As shown in Fig 5, the Proposed GPS-Free Model consistently achieves the lowest transmission delay compared to the other systems. The Blockchain and IoV model exhibits moderate delays, while the IoT Hardware model shows relatively higher latency. This indicates that the Proposed Model ensures faster communication and timely delivery of vehicle data. Such performance highlights its efficiency and superiority in minimizing transmission delays.

E. Transmission Accuracy

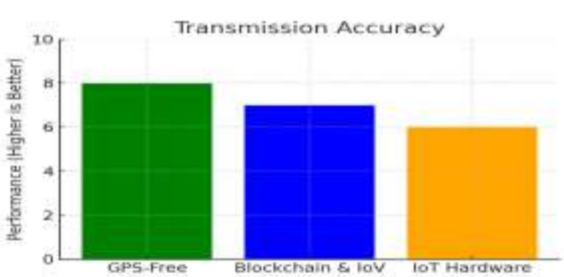


Fig 6: Transmission Accuracy

As shown in Fig 6, the Proposed Model consistently delivers the highest transmission accuracy compared to the other systems. The Blockchain and IoV model achieves moderate accuracy with occasional inconsistencies, while the IoT Hardware model shows relatively lower precision in data transmission. This demonstrates that the Proposed Model ensures reliable delivery of information with minimal errors. Such performance highlights its superiority in maintaining consistent and accurate transmissions.

F. Vehicle Location Tracking Accuracy

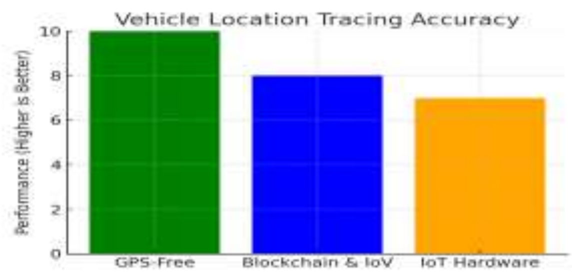


Fig 7: Vehicle Location Tracking Accuracy.

As shown in Fig 7, the Proposed Model consistently achieves the highest vehicle location tracing accuracy among the compared systems. The Blockchain and IoV model provides moderate accuracy, while the IoT Hardware model demonstrates relatively lower precision in identifying exact locations. This indicates that the Proposed Model ensures more accurate and dependable vehicle tracking through efficient GSM-based triangulation. Such performance highlights its robustness and superiority in precise vehicle location determination.

V. CONCLUSION

According to the study, the suggested GPS-Free car tracing system, which makes use of GSM modules and cell tower triangulation, performs better than current options like Blockchain & IoV and IoT-based vehicle tracking systems on a number of important performance parameters. By maximizing the utilization of existing communication channels, reducing congestion, and guaranteeing smooth data flow, the GPS-Free system demonstrates exceptional efficiency in terms of channel usage. The system maintains relatively minimal communication conflicts, which guarantees stable and dependable data delivery even in situations with significant traffic, according to the collision rate analysis.

The suggested system continuously handles vehicle position inquiries more quickly and accurately in terms of request processing accuracy, demonstrating its resilience in handling requests error-free. Likewise, the system exhibits low transmission latency, allowing for fast delivery of vital data and real-time vehicle tracking. Reliable vehicle monitoring requires that data packets be delivered and received accurately with little loss or corruption, which is ensured by optimizing transmission accuracy.

Finally, the vehicle location tracking accuracy metric emphasizes the effectiveness of GSM-based triangulation in providing precise and dependable vehicle positioning, surpassing the performance of both Blockchain & IoV and IoT-based systems. Overall, the proposed GPS-Free model exhibits a balanced combination of efficiency, reliability, and accuracy, making it practical and cost-effective solution for vehicle tracking without the need for GPS infrastructure. Its superior performance across all evaluated metrics underscores its potential for widespread adoption in intelligent transportation and fleet management systems.

REFERENCE

1. K. Ibraheem and S. W. Hadi, "Design and Implementation of a Low-Cost Secure Vehicle Tracking System," 2018 International Conference on Engineering Technology and their Applications(IICETA), Al-Najaf, Iraq, 2018, pp. 146-150, doi:10.1109/IICETA.2018.8458096.
2. R. Gao et al., "Glow in the Dark: Smartphone Inertial Odometry for Vehicle Tracking in GPS Blocked Environments," in IEEE Internet of Things Journal, vol. 8, no. 16, pp. 12955-12967, 15 Aug.15, 2021, doi: 10.1109/JIOT.2021.3064342.
3. E. Choi and S. Chang, "A consumer tracking estimator for vehicles in GPS-free environments," in IEEE Transactions on Consumer Electronics, vol. 63, no. 4, pp. 450-458, November 2017, doi: 10.1109/TCE.2017.015064.
4. V. Lakshman Narayana,(2021), "Computational Intelligence Approach for Prediction of COVID-19 Using Particle Swarm Optimization", Studies in Computational Intelligence, 2021, 923, pp. 175–189.
5. Anusha, P. & Ravikiran, A. & Narayana, V. & Maddumala, V.R.. (2020). Energy priority with on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2024.
6. Lakshman Narayana, V., Rao, G.S., Gopi, A.P., Lakshmi Patibandla, R.S.M. (2022). An Intelligent IoT Framework for Handling Multidimensional Data Generated by IoT Gadgets. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_9
7. ChandanaMuppalla, ShaikKhaderZelani, and D. VijayaSaradhi. "Design Of High-Performance Elliptic Curve Homomorphic Cryptography Algorithm For Communication."Efflatounia Journal, March 2019. ISSN: 1110-8703. Web of Science (WOS).
8. Sujatha, V., Y. Prasanthi, C. H. Pravallika, S. D. Jani Nasima, S. K. Ayesha Banu, and M. Sahithi. "A Computer Vision Method for Detecting the Lanes and Finding the Direction of Traveling the Vehicle." Lecture Notes in Networks and Systems, vol. 612, Springer, 2023, p. 373-382. https://doi.org/10.1007/978-981-19-9228-5_31
9. Devi, M.V., Harshitha, S., Ramya, K.L., Latha, B.H., Pranathi, P. International Conference on Artificial Intelligence for Innovations in Healthcare Industries, ICAIIHI 2023, 2023
10. Ekkurthi, Adinarayana, V. Sujatha, and K. Vijay Kumar. "Effective Moving Object Tracking Using Adaptive Background Subtraction with Advanced Probability Evolutionary Algorithm." International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 9S, 31 Aug. 2023, https://doi.org/10.17762/ijritcc.v11i9s.7389.
11. K. Sarada, V. Lakshman Narayana,(2020),"An Iterative Group Based Anomaly Detection Method For Secure Data Communication in

Networks",Journal of Critical Reviews,Vol 7, Issue 6, pp:208-212.doi: 10.31838/jcr.07.06.39.

12. Patibandla, R.S.M.L., Narayana, V.L., Gopi, A.P. (2021). Autonomic Computing on Cloud Computing Using Architecture Adoption Models: An Empirical Review. In: Choudhury, T., Dewangan, B.K., Tomar, R., Singh, B.K., Toe, T.T., Nhu, N.G. (eds) Autonomic Computing in Cloud Resource Management in Industry 4.0. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-71756-8_11
13. V. Pavani, S. Triveni, G. L. Madhuri, B. K. Priya, N. Bhargavi and G. Nayomi, "An Advanced Imaging and Machine Learning Algorithm for Enhanced Oral Cancer Detection," 2025 International Conference on Machine Learning and Autonomous Systems (ICMLAS), Prawet, Thailand, 2025, pp. 285-294, doi: 10.1109/ICMLAS64557.2025.10967776.
14. Varshini, Y., Mounika, T., Kumari, G. R. P., Sirisha, G., & Deepthi, Y. (2023, March). Crop Yield Forecast Using Machine Learning. In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 2310-2315). IEEE.
15. Krishna, P. Sandhya, Sk Reshmi Khadherbhi, and Vellalachervu Pavani. "Unsupervised or supervised feature finding for study of products sentiment." International Journal of Advanced Science and Technology 28, no. 16 (2019): 1916-1928.
16. BABU, J. R., REDDY, B. P., SRINIVAS, V. S., SREENIVASULU, A., RAMAKRISHNA, K., SATYANARAYANA, D., & VARAPRASAD, C. (2023). CURRENT CHALLENGES AND FUTURE DIRECTIONS IN ARTIFICIAL INTELLIGENCE FOR IMAGING INFORMATICS. Journal of Theoretical and Applied Information Technology, 101(21).
17. Chaitanya, P. Silpa, KV Narasimha Reddy, and G. Madhavi. "Effective Search of Color-Spatial Image Using Semantic Indexing." International Journal of Computer Science, Engineering and Applications (IJCSEA) Vol 2 (2012): 9-19.
18. H. Zhong, Y. Wang, Z. Miao, L. Li, S. Fan and H. Zhang, "A Homography-Based Visual Servo Control Approach for an Underactuated Unmanned Aerial Vehicle in GPS-Denied Environments," in IEEE Transactions on Intelligent Vehicles, vol. 8, no. 2, pp. 1119-1129, Feb. 2023, doi: 10.1109/TIV.2022.3163315.
19. M. A. Javed, M. Tahir and K. Ali, "Attitude in Motion: Constraints Aided Accurate Vehicle Orientation Tracking in Harsh Environment," in IEEE Transactions on Industrial Informatics, vol. 19, no. 5, pp. 6450-6459, May 2023, doi: 10.1109/TII.2022.3181798.
20. A. I. Basuki, M. F. Sidiq, T. I. Salim, A. I. Haris, T. I. Ramdhani and I. D. Bisulthon, "Secure Vehicle Tracking Using Blockchain and IoV," 2024 IEEE International Conference on Smart Mechatronics (ICSMech), Yogyakarta, Indonesia, 2024, pp. 255-259, doi: 10.1109/ICSMech62936.2024.10812292.
21. Kavishwar, S. (2011). Pension funds as an infrastructure financing avenue: An exploratory study. Management Dynamics, 11(2), 33-45.
22. Bidwaikar, V. N., & Kavishwar, D. S. (2012). Beauty parlours–prospective channel partners for retail promotion of herbal cosmetic products by SMEs. Indian Streams Research Journal. 2(1), 1-4
23. Shahu, A., Tiwari, H., Joshi, M., & Kavishwar, S. An Analysis of the Effectiveness of Index ETFS and Index Derivatives in Covered Call Strategy. Journal of Informatics Education and Research. 4(3), 42-48.
24. Jingar, N. K. (2026, February 13). Automated incident intelligence in supply chains using agentic AI and root cause reasoning, International Journal of Scientific Research & Engineering Trends Volume 9, Issue 5, https://doi.org/10.5281/zenodo.18162511
25. Jingar, N. K. (2022). Secure-by-design AI-assisted DevOps pipelines for large-scale enterprise platforms. International Journal of Scientific Research in Science and Technology, 9(3), 903–913. https://doi.org/10.32628/IJSRST2291348
26. R. Eswarawaka, M. Nijim, V. Kanumuri and H. Albetaineh, "Assessing the Efficacy of Machine Learning and Deep Learning in the Field of Cyber

Security," 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 2398-2404, doi: 10.1109/CSCE60160.2023.00388.

27. M. Nijim, V. Kanumuri, H. Albetaineh and A. Goyal, "Intelligent Monitoring and Management of Smart Buildings Using Machine Learning: Optimizing User Behavior and Energy Efficiency," 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 2391-2397, doi: 10.1109/CSCE60160.2023.00387.
28. Racha, Ganesh. “Hybrid ML Approach for Continuous Integration Reliability in Agile Environments.” United International Journal of Engineering and Sciences (UIJES), vol. 5, no. 3, 2025, pp. 9–21.
29. Racha, Ganesh. “Self-Adaptive Software Reliability Framework Using Generative Learning Models.” International Journal for Modern Trends in Science and Technology, vol. 12, no. 1, 2026, pp. 30–37.
30. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.
31. Veginati, Navya. “Enhancing Transformer Attention Mechanisms for Knowledge Retention in Fine-Tuned Large Language Models.” International Journal of Scientific Research in Science and Technology, vol. 11, no. 5, Sept.–Oct. 2024, pp. 864–871. DOI: https://doi.org/10.32628/IJSRST52310284
32. Jonnalagadda, Pawan Kalyan. “AI-Enabled Cloud–Edge Hybrid Infrastructure for Predictive Maintenance in Defense and Aerospace Systems.” International Journal of Science, Engineering and Technology, vol. 12, no. 2, 2024.
33. Jonnalagadda, Pawan Kalyan. “Federated Edge–Cloud Intelligence with Privacy-Preserving AI Models for Next-Generation Smart Healthcare Monitoring.” United International Journal of Engineering and Sciences (UIJES), vol. 5, no. 4, Dec. 2025, pp. 46–57.
34. Mahida, A. 2024. Integrating Observability With Devops Practices in Financial Services Technologies: A Study on Enhancing Software Development and Operational Resilience. International Journal of Advanced Computer Science & Applications, 15.
35. A. Mahida, "An Intellectual Zero Trust Security Framework Using Deep Reinforcement Learning for Predictive Threat Mitigation in AI-Based Fraud Detection Systems," in IEEE Access, vol. 14, pp. 24602-24617, 2026, doi: 10.1109/ACCESS.2026.3664389.
36. Tummuri, S. S. R. (2024). Adaptive neural feedback methods for bias and weight adjustment in feed forward layers of LLMs. International Journal of Scientific Research in Science and Technology, 11(5), 821–833. https://doi.org/10.32628/IJSRST52310380
37. Tummuri, S. S. R. (2023). Quantization aware training techniques for efficient transformer-driven large language models. International Journal of Scientific Research & Engineering Trends, 9(2).
38. A. Joon, B. K. R. Janumpally, A. Gogineni and P. Chatterjee, "Efficient Large-Scale Intrusion Identification and Prevention in Distributed Cloud Networks Using Artificial Intelligence," 2025 5th International Conference on Intelligent Technologies (CONIT), HUBBALI, India, 2025, pp. 1-8, doi: 10.1109/CONIT65521.2025.11167760.
39. B. K. Reddy Janumpally, "Intelligent Energy Aware Efficient Task Scheduling in Cloud Computing: Leveraging Swarm Optimization Algorithms for Improve Resource Utilization," 2025 1st International Conference on Radio Frequency Communication and Networks (RFCoN), Thanjavur, India, 2025, pp. 1-6, doi: 10.1109/RFCoN62306.2025.11085278.
40. Arora AS, Yachamaneni T, Kotadiya U. Optimizing Multi-Tenant Resource Allocation in Cloud-Based Distributed Systems for Large-Scale AI Model Training Using In-Memory Computing. IJERET [Internet]. 2021 Mar. 30 [cited 2026 Apr. 2];2(1):37-46.

ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science,
Engineering and Technology
An Open Access Journal

41. Kotadiya U, Arora AS, Yachamaneni T. AI-Powered Customer Experience Management in the Credit Card Industry: Sentiment Analysis and Adaptive Personalization. IJETCSIT [Internet]. 2021 Jun. 30 [cited 2026 Apr. 5];2(2):35-44.