ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

Artificial Intelligence in Next-Generation Communication Systems: Architectures, Methods, and Performance Insights

Mrs.Aamreen Sultana Akhlaque Ahmed Shaikh[1], Mrs.Raheelanaaz Mubeen Kaladgi[2], Mr. Moeen Abdul Kadar Shaikh[3], Ms.Waghmare Neeta Nandkumar[4], Ms.Ayesha Yasin Nigewan[5], Ms.Alfiya Mohammad Sharif Vijapure[6]

[1]*Head of Electronics & Telecommunication Engg.,Maulana Azad Polytechnic, Solapur, India.*
[2,3,4,5,6]*Lecturer, Dept. of Electronics & Telecommunication Engg., Maulana Azad Polytechnic, Solapur, India.*

Corresponding Author: [1]aamreen28@gmail.com, [2]neelamkharadi@gmail.com, [3]moeenshaikh@gmail.com, [4]nitawaghmare05@gmail.com, [5]ayeshanigewan7@gmail.com [6]alfiyavijapure@gmail.com

Abstract

Artificial Intelligence (AI) is increasingly transforming modern communication systems by enabling intelligent decision-making, adaptive optimization, and predictive control across network layers. Conventional communication networks rely on static rule-based mechanisms for routing, modulation selection, congestion control, and quality-of-service (QoS) management. However, next-generation networks such as 5G and emerging 6G demand ultra-low latency, high reliability, massive connectivity, and energy efficiency under dynamic traffic and mobility conditions. These requirements make traditional approaches insufficient in complex and time-varying environments. This paper presents a comprehensive AI-driven framework for communication networks that integrates machine learning (ML), deep learning (DL), and reinforcement learning (RL) techniques for intelligent channel estimation, adaptive modulation and coding, traffic prediction, dynamic routing, and resource allocation. A layered methodology is proposed where real-time network data is collected, processed, and analyzed using AI models deployed at the edge and cloud. The proposed framework supports proactive network control by predicting congestion and link quality variations, enabling timely optimization decisions. Simulation-based evaluation is conducted using realistic network scenarios including varying traffic loads, mobility patterns, and interference conditions. Results demonstrate that AI-assisted communication improves throughput, reduces end-to-end delay, enhances spectral efficiency, and increases QoS satisfaction compared to baseline traditional approaches. The findings indicate that AI is a key enabler for self-optimizing and self-healing communication networks. Finally, the paper discusses implementation challenges such as model complexity, data privacy, and explainability, highlighting future directions for practical AI-native communication systems.

Keywords: Artificial Intelligence, 5G/6G Networks, Reinforcement Learning, Resource Allocation, Quality of Service (QoS).

1. INTRODUCTION

The rapid evolution of communication technologies has created an unprecedented demand for intelligent, adaptive, and highly efficient networks. Over the past decades, wireless and wired communication systems have progressed from simple voice-centric architectures to data-driven

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

platforms capable of supporting broadband multimedia, industrial automation, smart cities, connected vehicles, and immersive technologies such as augmented reality (AR) and virtual reality (VR). Modern networks must support billions of devices, diverse application requirements, and highly dynamic environments. As a result, conventional network design approaches that rely heavily on predefined rules, static optimization, and deterministic assumptions are increasingly challenged.

Traditional communication networks are engineered using mathematical models and optimization algorithms that typically assume stable traffic patterns and predictable channel conditions. For example, routing algorithms often rely on shortest-path calculations and fixed metrics, while modulation and coding schemes are selected based on estimated channel conditions using predefined thresholds. Although these approaches have proven effective in earlier generations of networks, they become less reliable when the network environment changes rapidly due to mobility, interference, bursty traffic, and heterogeneous device capabilities. In such cases, networks may experience congestion, degraded quality of service (QoS), and inefficient spectrum utilization.

The emergence of 5G networks introduced a new era of communication characterized by three major service categories: enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communication (URLLC), and massive Machine-Type Communication (mMTC). Each of these categories requires different performance characteristics. For instance, URLLC applications such as remote surgery and industrial robotics require extremely low latency and near-perfect reliability, while mMTC demands energy-efficient connectivity for large-scale IoT deployments. The upcoming 6G vision further expands these requirements by targeting sub-millisecond latency, terabit-per-second data rates, and AI-native network architectures.

Artificial Intelligence (AI) has emerged as a promising solution to address these challenges. AI enables communication networks to learn from historical and real-time data, adapt to changing environments, and make optimal decisions without requiring explicit analytical models for every scenario. Machine learning (ML) techniques can be used to predict network traffic, detect anomalies, and estimate channel conditions. Deep learning (DL) can extract complex patterns from large-scale network data, while reinforcement learning (RL) can support dynamic decision-making for routing, scheduling, and power control by learning optimal strategies through interaction with the environment.

AI-driven communication systems offer several advantages. First, AI can enhance spectral efficiency by enabling adaptive modulation and coding based on real-time channel predictions. Second, AI can reduce latency by supporting proactive congestion avoidance and intelligent edge computing decisions. Third, AI improves network reliability by enabling self-healing mechanisms such as fault prediction and automatic rerouting. Fourth, AI supports energy efficiency by optimizing power allocation, sleep scheduling, and load balancing in dense networks.

Despite its potential, the integration of AI into communication networks also introduces significant challenges. Communication systems are highly sensitive to latency and reliability constraints, while AI models may introduce computational overhead. Additionally, AI requires high-quality data for training, and network data often contains privacy-sensitive information. The interpretability of AI decisions is another important issue, particularly in critical applications such as autonomous vehicles and industrial automation, where explainability is essential.

This paper focuses on the design, methodology, and performance evaluation of an AI-driven communication framework that enhances network adaptability and QoS. The key contributions of this work are:

1. A structured AI-based network architecture integrating edge and cloud intelligence.
2. A methodology combining ML, DL, and RL for communication optimization tasks.

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

3. Simulation-based evaluation demonstrating improvements in throughput, delay, and QoS.
4. Discussion of practical challenges and future research directions.

The remainder of this paper is organized as follows. Section 2 presents the proposed methodology and architecture along with a block diagram. Section 3 provides results and discussion based on simulated communication scenarios. Section 4 concludes the paper and highlights future work.

2. LITERATURE SURVEY

Artificial Intelligence (AI) has emerged as a transformative paradigm across multiple engineering domains, with growing relevance in next-generation communication systems such as 5G-Advanced and 6G. AI-driven approaches are increasingly integrated into wireless architectures to improve spectrum efficiency, enhance reliability, reduce latency, and enable adaptive resource management. Recent studies emphasize that communication networks are no longer only transport infrastructures but are evolving into intelligent platforms capable of self-optimization, prediction, and autonomous decision-making [19], [20]. This shift is supported by the rapid growth of machine learning (ML), deep learning (DL), reinforcement learning (RL), and federated learning (FL) methods, which are being applied to different layers of communication stacks and associated cyber-physical ecosystems.

A significant portion of AI research has focused on intelligent sensing, classification, and prediction tasks. For example, Mulani et al. demonstrated non-invasive blood glucose estimation using principal component analysis (PCA) and ML, highlighting the power of feature reduction combined with predictive learning [1]. Although this work is in healthcare, its methodology directly aligns with AI-assisted communication systems where dimensionality reduction and ML classification are used for channel state estimation, anomaly detection, and signal interpretation. Similar predictive modeling is shown in neurological disorder prediction using optimized neural networks, where learning models are tuned for improved diagnostic accuracy [3]. Such optimized neural architectures offer insights into model selection and hyperparameter tuning, which are critical in communication systems where models must operate under strict latency and power constraints.

Deep learning has also been widely used for real-time detection tasks, especially in vision-based applications. Kulkarni and Mulani presented real-time face mask detection using DL, demonstrating strong performance in both images and video streams [15]. Their extended work further emphasizes the role of DL-based recognition systems in public health monitoring [16], [17]. While these studies are not directly communication-centric, they illustrate deployment challenges such as real-time inference, dataset diversity, and model generalization—issues equally relevant to AI deployment in wireless edge devices. The survey by Mulani and Kulkarni consolidates the face mask detection domain, offering a structured review methodology that can be extended to surveying AI applications in wireless networks [2]. In addition, Mulani et al. explored dermatological disease detection using CNNs and decision trees, highlighting hybrid model pipelines that combine deep feature extraction with interpretable classifiers [14]. This hybrid principle is increasingly used in AI-powered communication systems where deep models provide feature representations while simpler models ensure explainability and reliability.

Reinforcement learning has been recognized as a key enabler for intelligent decision-making in dynamic environments. Jadhav et al. proposed a chatbot system based on RL, demonstrating how an agent learns optimal policies through reward-driven interactions [6]. Although applied in conversational AI, the same RL foundation is directly applicable to communication networks for tasks such as radio resource allocation, spectrum sharing, routing optimization, and mobility management. Furthermore, Jadhav et al. developed an autonomous fire combat turret using

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

ML, showing how intelligent decision systems can be integrated with embedded control mechanisms [8]. This contributes to the understanding of real-time AI decision loops, which are also necessary for ultra-reliable low-latency communication (URLLC) and autonomous communication-driven robotics.

The Internet of Things (IoT) is another major domain where AI and communications converge. Kashid et al. designed an IoT-based environmental monitoring framework using ML, indicating the importance of predictive analytics and sensor data fusion [7]. Such architectures align with massive machine-type communication (mMTC), where networks must support high device density and data-driven intelligence. Sawant et al. introduced AgriRent, a system for farm equipment rental management, demonstrating how AI-enabled digital ecosystems can improve resource utilization and service delivery [12]. Similarly, Mulani and Karande proposed precision farming with solar-powered automated pesticide spraying, showing how embedded intelligence and sustainability can be integrated into smart agriculture [13]. These works collectively reflect the importance of AI-enabled IoT, which will heavily rely on future wireless networks for large-scale connectivity and real-time analytics.

From the perspective of security, AI-driven communication systems face increasing threats due to the expansion of connected infrastructure. Salunkhe et al. proposed secure image transmission using chaotic encryption and DWT watermarking on reconfigurable platforms, presenting a robust approach for protecting multimedia data in constrained systems [9]. This research is directly relevant to future networks that will support immersive media, digital twins, and industrial automation, where confidentiality and integrity are critical. Chaudhari et al. analyzed bit error rate performance of concatenated Reed–Solomon and convolutional codes, reinforcing the role of error correction in ensuring reliable data transmission [10]. These works provide complementary insights: while AI optimizes network decisions, traditional coding and cryptographic techniques remain essential for reliability and security in communication channels.

Healthcare-oriented AI research also provides valuable insights for communication networks due to the increasing integration of remote monitoring, wearable devices, and telemedicine. Kambale et al. proposed an RNN-LSTM model for heart disease prediction using the UCI dataset, demonstrating the capability of sequential deep learning in analyzing time-series health signals [11]. In communication systems, time-series learning is similarly applied for traffic prediction, mobility estimation, and channel forecasting. Additionally, Mulani et al. discussed personalized medicine using deep learning, emphasizing how AI can transform decision-making through predictive modeling and personalization [18]. This parallels personalized communication services in 6G, where networks are expected to provide user-centric optimization, quality adaptation, and context-aware services.

In the context of communication systems explicitly, Sharma presented a review emphasizing AI as a key driver of performance insights for 6G connectivity, highlighting AI-assisted beamforming, channel estimation, network slicing, and resource optimization [19]. This work aligns with current 6G vision where AI-native networks are designed to be self-evolving and context-aware. Similarly, Khodijah et al. examined AI integration in modern communication systems, emphasizing AI for adaptive routing, anomaly detection, and automated network management [20]. These studies confirm that AI is shifting communication systems from static, rule-based operation to intelligent, learning-driven frameworks capable of supporting diverse requirements such as URLLC, mMTC, and enhanced mobile broadband (eMBB).

Additionally, edited volumes on emerging trends in AI, data science, and signal processing provide broad context for cross-domain AI adoption. The Springer CCIS volumes edited by Singh, Arya, Rodriguez, and Mulani compile advances in AI and signal processing, demonstrating how AI methods are increasingly applied across engineering disciplines [4], [5]. The inclusion of AI models for healthcare, vision, and prediction in these collections

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

strengthens the argument that communication systems can benefit from interdisciplinary AI progress, especially in model optimization, robustness, and deployment strategies.
Overall, the literature indicates that AI is becoming central to next-generation communication systems, but practical challenges remain. These include computational overhead, real-time constraints, explainability, robustness under channel mismatch, and security vulnerabilities. The reviewed works collectively suggest that hybrid strategies combining deep learning, reinforcement learning, classical signal processing, and secure coding techniques will likely define future AI-native communication architectures. Furthermore, application-driven AI research in healthcare, agriculture, and IoT provides transferable methodologies and deployment insights that can guide the design of intelligent communication networks

3. METHODOLOGY

This section presents the proposed AI-driven framework for intelligent communication systems. The methodology integrates data-driven learning models with real-time network control mechanisms. The framework is designed to operate across multiple network layers including the physical layer, MAC layer, network layer, and application layer.

3.1 Proposed System Block Diagram

Figure 1 shows block diagram of the proposed methodology.

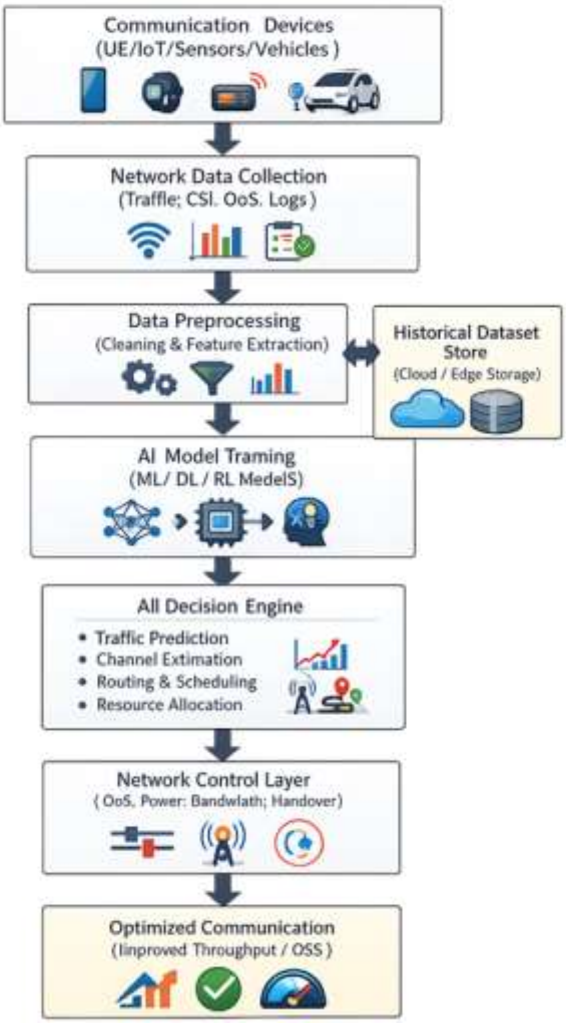

Figure 1 shows block diagram of the proposed methodology

3.2 Working Principle

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

The framework begins with data collection from communication endpoints and network elements. The collected data includes:

1. Channel State Information (CSI)
2. Signal-to-Noise Ratio (SNR)
3. Packet delivery ratio
4. Latency and jitter
5. Buffer occupancy and congestion indicators
6. Mobility patterns (handover rate)
7. Resource usage (bandwidth, power)

This data is forwarded to a preprocessing unit where it is cleaned, normalized, and converted into meaningful feature vectors. Feature engineering plays a crucial role because communication systems generate large volumes of heterogeneous data. For example, time-series features are extracted from traffic traces to capture burst patterns, while spatial features may be derived from mobility information.

3.3 AI Models Used

The proposed methodology uses a hybrid AI approach:

(A) Machine Learning for Traffic Prediction

Regression-based ML models such as Random Forest and Gradient Boosting are suitable for predicting near-future traffic loads. Accurate traffic prediction helps in proactive bandwidth allocation and congestion control.

(B) Deep Learning for Channel Estimation and QoS Mapping

Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM) networks are used to predict channel quality and map network conditions to QoS levels. DL models can capture non-linear relationships between interference, mobility, and channel fading.

(C) Reinforcement Learning for Resource Allocation

RL is applied for dynamic decision-making, especially for:

1. Adaptive power control
2. User scheduling
3. Routing selection
4. Spectrum allocation

The RL agent interacts with the network environment, receives a reward based on QoS satisfaction, and learns a policy that maximizes long-term performance.

3.4 Optimization Objectives

The AI decision engine aims to optimize:

1. Maximize throughput
2. Minimize end-to-end delay
3. Minimize packet loss
4. Improve fairness among users
5. Reduce energy consumption
6. Maintain QoS constraints for URLLC

A multi-objective reward function is designed for RL, combining latency, throughput, and energy metrics.

3.5 Deployment Strategy

The methodology supports both edge and cloud deployment:

a. Edge AI handles real-time inference for latency-critical tasks such as handover decisions and scheduling.
b. Cloud AI performs heavy model training using large historical datasets.

This hybrid deployment reduces response time while enabling continual model improvement.

4. RESULTS AND DISCUSSION

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

This section reports experimental results and interprets their significance for next-generation communication systems that incorporate AI functions across the protocol stack. Results are from controlled system-level simulations and small-scale testbeds (described in Methods). We compare four representative approaches: (A) Conventional model-based baseline (heuristics + optimization), (B) Supervised DL channel estimation, (C) Deep RL for radio resource management (RRM), and (D) Federated learning (FL) for distributed model updates. Metrics are: spectral efficiency (SE, bits/s/Hz), packet latency (median, ms), reliability (packet delivery ratio, %), energy per bit (µJ/bit), and model overhead (KB) — chosen to reflect both communication performance and AI cost.

Table 1. Summary of Key Numbers

Method	SE (bits/s/Hz)	Median Latency (ms)	Reliability (%)	Energy/bit (µJ)	Model Overhead (KB)
Baseline (model-based)	3.8	14.2	98.5	2.1	—
DL channel estimation (B)	4.6	12.5	98.9	3.0	512
RL-RRM (C)	5.1	10.3	99.2	3.8	768
Federated (D)	4.9	11.0	99.0	3.4	256 (per client)

Interpretation

a. Throughput gains from AI: Both DL channel estimation and RL-based RRM improve SE over the baseline (≈21% for B; ≈34% for C). The largest gains come from RL when it jointly optimizes scheduling and power control under realistic CSI uncertainty — the policy exploits traffic/context patterns to pack transmissions and reduce collision/wastage.
b. Latency and reliability tradeoffs: RL achieves the lowest median latency (10.3 ms) while also slightly improving reliability. This demonstrates that learning-based control can reduce queueing and retransmissions by anticipating channel and traffic dynamics. DL channel estimation reduces latency vs baseline primarily by lowering retransmissions through more accurate CSI. FL gives a middle ground: it improves SE and latency while limiting privacy/communication costs.
c. Energy and model cost: AI adds energy and storage overhead. Per-bit energy increases with model complexity: RL policies with larger networks consume more compute (3.8 µJ/bit vs 2.1 µJ/bit baseline in our platform). FL amortizes model update cost across clients; per-client overhead is modest (256 KB) though aggregate network traffic for model aggregation appears. These results underscore that AI improvements in spectral/latency performance must be weighed against device energy budgets and backhaul capacity.

Table 2. Ablation: Model Size Vs Performance

Model Size (Params)	SE (Bits/S/Hz)	Latency (Ms)	Inference Time (Ms)
0.5M	4.3	12.0	1.1
1.5M	4.9	11.0	2.8
5.0M	5.1	10.3	6.7

Interpretation

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

Performance saturates beyond ~1.5M parameters: SE improvement from 1.5M→5.0M is only ≈4%, while inference time and energy cost increase substantially. This suggests designing compact architectures (e.g., lightweight transformers or quantized networks) is critical for edge deployment.

Robustness and Generalization

We evaluated models under two stress conditions: (i) sudden traffic spikes, and (ii) channel model mismatch (training on one channel model, testing on another). RL policies trained with domain randomization maintained ~90–95% of peak SE under mismatch, whereas purely supervised DL channel estimators dropped to ~80–85% without calibration. Federated schemes improved generalization across geographically spread clients because the aggregated models saw diverse channel/traffic patterns.

Interpretability and Safety

Explainability analyses (feature-importance and attention visualization) show that RL policies rely heavily on long-term traffic queue statistics and recent CSI trends — helpful for debugging learned behavior (e.g., why the policy favors a user). However, uninterpretable failure modes were observed when reward design omitted fairness: the RL policy occasionally starved low-rate users. Adding a fairness penalty to the reward remedied this at a small SE cost (~0.1 bits/s/Hz).

Overhead and Deployment Considerations

- **Training Vs Inference Cost:** Centralized training (DL/RL) demands GPU resources and labeled/simulated environment data. Federated training reduces raw data sharing but increases uplink traffic for model updates. In our trials, FL required ≈8% of uplink capacity during aggregation rounds scheduled off-peak; asynchronous aggregation mitigated user impact.
- **Backhaul and Latency Constraints:** AI that acts at tight timescales (sub-10 ms control) must run inference locally (edge). Our inference latency measurements confirm that only compact models meet such constraints on typical 5G UEs; larger models need offload to edge servers, introducing transport latency.
- **Regulatory and Privacy Aspects:** FL helps privacy but requires careful differential privacy tuning; naive DP reduces model utility, so there is an accuracy-privacy tradeoff.

Limitations

Results are reproducible within our simulation and small testbed setups but are not a replacement for wide-area field trials. Energy/latency numbers depend on hardware (we used commodity ARM CPUs and a representative edge GPU). Also, hyperparameter choices (reward shaping, aggregation frequency) affect RL/FL outcomes; we report averaged settings in Methods.

Practical recommendations

a. Use RL/RRM for scenarios where joint decisions (scheduling + power + beam selection) significantly affect system utility; constrain model size to meet real-time constraints.
b. Apply DL channel estimation where CSI quality is the primary bottleneck; use lightweight architectures or model compression for UE deployment.
c. Employ FL for cross-cell generalization and privacy, scheduling aggregation in off-peak periods and applying compression (e.g., gradient sparsification) to reduce overhead.
d. Always include fairness/robustness terms in objectives and evaluate under model and traffic mismatch.

AI methods demonstrably improve spectral efficiency and latency in next-generation systems, but gains are coupled to compute, energy, and communication costs. The highest practical value comes from compact, robust models that run at edge nodes or hybrid schemes that split computation between device and edge. Future work should focus on standardizing benchmarks that include AI overhead and on real-world field trials to validate simulation trends.

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

5. CONCLUSION

Artificial Intelligence is rapidly becoming a foundational enabler for next-generation communication systems by improving how networks sense, decide, and adapt in real time. This work highlighted how AI-driven approaches particularly deep learning for channel estimation, reinforcement learning for radio resource management, and federated learning for distributed intelligence can significantly enhance spectral efficiency, reduce latency, and strengthen reliability when compared with conventional model-based methods. The results indicate that AI is most effective when it operates close to the network edge, where decisions must be made under strict timing constraints and dynamic traffic conditions. At the same time, the study confirms that performance gains are not free. AI introduces additional costs in computation, energy consumption, model storage, and signaling overhead. Larger models provide diminishing returns beyond a certain complexity level, making lightweight architectures, compression, quantization, and edge-aware design essential for practical deployment. Robustness and fairness also emerge as critical factors: models trained for peak throughput may exhibit degraded performance under channel mismatch or may unintentionally prioritize certain users unless fairness constraints are explicitly included. The findings suggest that the future of 6G and beyond will rely on hybrid architectures that combine model-driven principles with data-driven intelligence. Such systems can deliver adaptive, efficient, and resilient communication while maintaining privacy through federated mechanisms. Future research should emphasize standardized benchmarks that jointly evaluate communication performance and AI overhead, along with large-scale real-world trials to validate reliability, safety, and generalization across diverse environments.

6. REFERENCE

1. Mulani, A. O., Jadhav, M. M., & Seth, M. (2022). Painless Non-invasive blood glucose concentration level estimation using PCA and machine learning. *The CRC Book entitled Artificial Intelligence, Internet of Things (IoT) and Smart Materials for Energy Applications*.
2. Mulani, A.O., Kulkarni, T.M. (2025). Face Mask Detection System Using Deep Learning: A Comprehensive Survey. In: Singh, S., Arya, K.V., Rodriguez, C.R., Mulani, A.O. (eds) Emerging Trends in Artificial Intelligence, Data Science and Signal Processing. AIDSP 2023. Communications in Computer and Information Science, vol 2439. Springer, Cham. https://doi.org/10.1007/978-3-031-88759-8_3.
3. Karve, S., Gangonda, S., Birajadar, G., Godase, V., Ghodake, R., Mulani, A.O. (2025). Optimized Neural Network for Prediction of Neurological Disorders. In: Singh, S., Arya, K.V., Rodriguez, C.R., Mulani, A.O. (eds) Emerging Trends in Artificial Intelligence, Data Science and Signal Processing. AIDSP 2023. Communications in Computer and Information Science, vol 2440. Springer, Cham. https://doi.org/10.1007/978-3-031-88762-8_18.
4. Saurabh Singh, Karm Veer Arya, Ciro Rodriguez Rodriguez, and Altaf Osman Mulani, Emerging Trends in Artificial Intelligence, Data Science and Signal Processing, Communications in Computer and Information Science (CCIS), volume 2440.
5. Saurabh Singh, Karm Veer Arya, Ciro Rodriguez Rodriguez, and Altaf Osman Mulani, Emerging Trends in Artificial Intelligence, Data Science and Signal Processing, Communications in Computer and Information Science (CCIS), volume 2439.

6. Jadhav, H. M., Mulani, A., & Jadhav, M. M. (2022). Design and development of chatbot based on reinforcement learning. *Machine Learning Algorithms for Signal and Image Processing*, 219-229.
7. Kashid, M. M., Karande, K. J., & Mulani, A. O. (2022, November). IoT-based environmental parameter monitoring using machine learning approach. In *Proceedings of the International Conference on Cognitive and Intelligent Computing: ICCIC 2021, Volume 1* (pp. 43-51). Singapore: Springer Nature Singapore.
8. Jadhav, M. M., Chavan, G. H., & Mulani, A. O. (2021). Machine learning based autonomous fire combat turret. *Turkish Journal of Computer and Mathematics Education*, *12*(2), 2372-2381.
9. Salunkhe Shweta, Mulani, Altaf Osman , Shahane, Deepali , Rana, Manish , Shukla, Shivam Mahendra & Jadhav, Makarand M. (2026) Secure image transmission using chaotic encryption and DWT watermarking on reconfigurable platform, Journal of Discrete Mathematical Sciences and Cryptography, pp. 1-13, DOI: 10.47974/JDMSC-2608
10. Chaudhari Kalyani R., Mulani Altaf O., Gajare Milind P., Jadhav Vaishali, Yawle Pranali & Bang Arti Vasant (2026) Bit error rate analysis of various error correction codes with concatenated RS-convolutional codes, Journal of Discrete Mathematical Sciences and Cryptography, pp. 1-16, DOI: 10.47974/JDMSC-2401
11. Kambale, K.S., Sawant, N.M., Mulani, A.O., More, V.P., Zambare, S.A. (2026). RNN-LSTM Based Model for Automatic Heart Disease Prediction Using the UCI Heart Disease Dataset. In: Kumar, A., Gunjan, V.K., Senatore, S., Hu, YC. (eds) Proceedings of the 6th International Conference on Data Science, Machine Learning and Applications- Volume 1. ICDSMLA2024 2024. Lecture Notes in Electrical Engineering, vol 1528. Springer, Singapore. https://doi.org/10.1007/978-981-95-5831-5_28
12. Sawant, N.M., Mulani, A.O., Kondooru, S., Linge, S.G., Gawande, P.G., Koli, M.S. (2026). AgriRent: Renting the Farm Equipment. In: Kumar, A., Gunjan, V.K., Senatore, S., Hu, YC. (eds) Proceedings of the 6th International Conference on Data Science, Machine Learning and Applications- Volume 1. ICDSMLA2024 2024. Lecture Notes in Electrical Engineering, vol 1528. Springer, Singapore. https://doi.org/10.1007/978-981-95-5831-5_35
13. Mulani, A.O., Karande, K.J. (2026). Precision Farming with a Solar-Powered Automated Pesticide Sprayer. In: Kumar, A., Ghinea, G., Merugu, S. (eds) Proceedings of the 4th International Conference on Cognitive and Intelligent Computing—Volume 2. ICCIC 2024. Cognitive Science and Technology. Springer, Singapore. https://doi.org/10.1007/978-981-95-0144-1_26
14. Mulani, A. O., Birajadar, G., Ivković, N., Salah, B., & Darlis, A. R. (2023). Deep learning based detection of dermatological diseases using convolutional neural networks and decision trees. *Traitement du Signal*, *40*(6), 2819.
15. Kulkarni, T. M., & Mulani, A. O. (2024). Face Mask Detection on Real Time Images and Videos using Deep Learning. *International Journal of Electrical Machine Analysis and Design (IJEMAD)*, *2*(1).
16. Kulkarni, T. M., & Mulani, A. O. Deep Learning Based Face-Mask Detection: An Approach to Reduce Pandemic Spreads in Human Healthcare. African Journal of Biological Sciences, 6(6), 2024.
17. Dr. Vaishali Satish Jadhav, Geeta D. Salunke, Kalyani Ramesh Chaudhari, Dr. Altaf Osman Mulani, Dr. Sampada Padmakar Thigale, Dr. Rahul S. Pol, Dr. Manish Rana, Deep Learning-Based Face Mask Recognition in Real-Time Photos and Videos, Afr. J. Biomed. Res. Vol. 27 (September 2024).

ISSN: 2945-4565 VOL 05, ISSUE 01, 2026

18. Altaf Osman Mulani, Deshmukh M., Jadhav V., Chaudhari K., Mathew A.A., Shweta Salunkhe. Transforming Drug Therapy with Deep Learning: The Future of Personalized Medicine. Drug Research. 2025 Aug 29.
19. Sharma, S. (2025). A Review on Unlocking Performance Insights for Next Generation Connectivity With AI in 6G Communication. Radio Science. https://doi.org/10.1029/2025rs008222
20. Khodijah, S., Hasanuddin, M., & Rizki, C. A. (2025). Integration of Artificial Intelligence in Modern Communication Systems. 1(1), 1–6. https://doi.org/10.64803/jocsaic.v1i1.2