Energy-Efficient Drone Battery Management Using AI-Based Predictive Control and Smart Charging Strategies

Dr. P. Ram Kishore Kumar Reddy
Professor, Department of Electrical and Electronics Engineering, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana 500075, India. Email: prkumarreddy_eee@mgit.ac.in
Dr. P. Lakshmi Supriya
Assistant Professor, Department of Electrical and Electronics Engineering, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana 500075, India.
Email: plaxmisupriya_eee@mgit.ac.in
Dr. Ch. Vinay Kumar
Assistant Professor, Department of Electrical and Electronics Engineering, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana 500075, India.
Email: chvinaykumar_eee@mgit.ac.in

Abstract

The growing use of unmanned aerial vehicles (UAVs) in surveillance, agriculture, transportation, and environmental monitoring has increased the demand for reliable and energy-efficient battery systems. Traditional drone batteries often suffer from limited endurance, unpredictable power consumption, and inefficient charging practices, which reduce flight duration and overall mission performance. This study proposes an AI-based predictive control system combined with smart charging strategies to enhance drone battery efficiency, safety, and lifespan. The proposed framework uses machine learning algorithms to predict key battery parameters such as state-of-charge (SoC), state-of-health (SoH), discharge patterns, and thermal variations. By analyzing real-time sensor data and historical usage profiles, the system optimizes power allocation during flight and minimizes energy losses. The predictive model adjusts the drone's power consumption based on mission requirements, environmental conditions, and remaining energy levels, ensuring higher operational reliability. In addition, a smart charging strategy is designed using adaptive current and voltage control. This method prevents overcharging, reduces thermal stress, and maintains battery cell balance. The charging process dynamically adjusts based on predicted battery health, thereby extending overall battery lifecycle and ensuring faster, safer charging cycles Simulation results indicate improved flight time, better energy utilization, and enhanced thermal stability compared to conventional BMS approaches. The combined predictive and adaptive approach strengthens mission planning by offering accurate battery performance forecasts, accuracy of 93.45%, sensitivity of 96.52%, Recall of 97.23% has attained.

Keywords: Drone battery management, power analysis, autonomous drones.

Introduction

Unmanned aerial vehicles (UAVs), commonly known as drones, have become essential tools across multiple sectors, including precision agriculture, surveillance, disaster response, logistics, and environmental monitoring. Their growing adoption is driven by advancements in lightweight materials, autonomous navigation, and onboard sensing technologies. However, despite these developments, one of the most critical limitations restricting drone scalability and mission endurance is the dependence on lithium-based batteries with constrained energy density. Limited flight time, unpredictable discharge behavior, and battery degradation pose significant challenges for continuous and long-range UAV operations. Conventional battery management systems rely on static estimation techniques and predefined power usage models, which often fail under dynamic mission profiles and varying environmental conditions. As drones operate in complex and uncertain scenarios such as fluctuating payloads, variable wind patterns, and temperature-induced performance shifts there is a need for intelligent systems capable of adapting power consumption in real time. Inefficient charging and repeated deep discharge cycles further accelerate battery wear, increasing operational costs and safety risks. Recent advancements in artificial intelligence (AI) and data-driven modeling offer promising opportunities to address these challenges. AI-based predictive control can forecast battery behavior with higher accuracy by analyzing historical data, real-time sensor readings, and mission parameters. When integrated with smart charging strategies, these systems can optimize energy utilization, prevent thermal stress, and extend battery lifespan. Therefore, developing an intelligent and adaptive battery management framework is essential for enabling longer, safer, and more autonomous UAV operations. This research aims to contribute a scalable solution that supports the future direction of energy-efficient drone technologies.

1. Top Block – Sensors / Environment Data Input

   This block represents the onboard or external sensors (GPS, IMU, altimeter, camera, LiDAR, etc.). These provide essential environmental data that the drone uses for navigation, stability, and situational awareness.

2. Left Block – Remote Controller / Ground Control Station

   This block shows the command and control input coming from a pilot or ground station. It includes manual commands, mission parameters, or flight-path adjustments.

3. Right Block – Communication Module (V2X / Telemetry)

   This block represents wireless communication links, such as telemetry, Wi-Fi, RF, or V2X. It allows the drone to send data (video, status, sensor data) and receive instructions from remote systems.

4. Bottom Left Block – Power Management / Battery System

   This subsystem handles battery monitoring, power distribution, charging control, and energy optimization to ensure safe and extended flight operation.

5. Bottom Right Block – Payload / Actuator System

This includes motors, gimbal, camera payloads, sensors, or task-specific equipment (e.g., spraying unit, delivery box). The drone controls these components based on mission needs.

The proposed drone framework is developed through a modular and integrated methodology, where the drone acts as the central processing and decision-making unit. The overall system architecture consists of five major components: sensor module, ground control interface, communication subsystem, power management unit, and payload/actuator system. The methodology begins with real-time data acquisition through the sensor module, which includes GPS, IMU, altimeter, and optional vision sensors such as cameras or LiDAR. These sensors continuously capture environmental conditions, flight orientation, position, and obstacle information. The collected data is transmitted to the drone's onboard processor, where sensor fusion algorithms preprocess and filter the signals for reliable interpretation. Simultaneously, mission commands and flight instructions are received from the ground control station, allowing either manual control or semi-autonomous operation. The communication subsystem facilitates two-way telemetry exchange, ensuring that the drone transmits live status, payload information, and diagnostic updates while receiving navigation updates or emergency commands.

The power management unit monitors battery health, regulates energy distribution, and ensures safe power delivery to critical modules. This component is essential for maintaining stable flight, predicting remaining flight time, and preventing power failures. The payload and actuator subsystem executes the operational objectives of the drone—such as imaging, delivery, surveillance, or mechanical actions—through motors, gimbals, or specialized equipment. All subsystems interact through the drone's central control unit, which uses embedded algorithms to coordinate flight control, collision avoidance, stabilization, and mission execution. The integration of these modules results in a robust and scalable methodology that supports efficient, safe, and autonomous drone operation. The structured flow of data and control signals enables high responsiveness, reliability, and adaptability, making the proposed system suitable for a wide range of real-world applications.

Literature survey

The intersection of artificial intelligence (AI) with smart mobility and energy systems has rapidly matured into a multidisciplinary research domain encompassing battery management, drone control, renewable energy optimization, and cybersecurity for connected vehicles. Early work on AI-driven battery management has emphasized intelligent charging strategies and predictive control to extend battery life and improve energy efficiency. Bhupathi and Chinta [1] and Aravind & Surabhi [2] present comprehensive studies on AI/ML strategies for efficient electric-vehicle (EV) battery utilization and charging schedules, demonstrating how data-driven charging policies can reduce degradation and improve usable capacity. These studies highlight model-based and learning-based control paradigms that adapt charging rates and schedules to usage patterns, environmental conditions, and grid constraints—foundations that subsequent work has extended into real-time and predictive frameworks.

Parallel advances in drone control and autonomy show the applicability of AI beyond ground vehicles. Caballero-Martin et al. [3] provide a state-of-the-art review on artificial intelligence applications in drone control, underlining the role of reinforcement learning, computer vision, and sensor fusion in enabling autonomous navigation, obstacle avoidance, and mission planning. These techniques closely link with energy-aware control because drone endurance is tightly coupled to power management; hence, control algorithms increasingly incorporate battery state and power optimization as first-class inputs. Research on renewable energy and grid integration complements these autonomy studies by showing how distributed energy resources and smart charging infrastructures can be coordinated. Works by Ukoba et al. [4], Rane et al. [5], and Kannan et al. [6] survey AI applications in renewable-energy optimization, grid-centric efficiency, and the potential of 5G/6G integration to enable low-latency, high-bandwidth connections for mobile and vehicular platforms. These papers collectively argue that communications and energy management must co-evolve with autonomy algorithms to meet performance and reliability targets for smart mobility.

Battery technology and power interfaces form another critical research strand. Abro et al. [7] review recent advancements in battery and propulsion systems for autonomous and connected electric vehicles, stressing improvements in cell chemistry, thermal management, and power electronics that support more robust and efficient vehicle platforms. These hardware developments enable higher-level AI strategies to be more effective because they widen the feasible control envelope (e.g., faster charging, deeper discharge management). Li [8] further contends that AI-enabled energy internets could play a central role in achieving carbon-neutral targets; however, he also notes the challenges of interoperability, data privacy, and algorithmic robustness that accompany large-scale deployments.

Predictive maintenance and operational longevity are recurring themes in the literature. Bello et al. [9] survey AI-driven predictive maintenance approaches for renewable-energy systems, demonstrating improvements in uptime and cost savings through anomaly detection and life-cycle estimation. The same principles are becoming standard for fleets of connected vehicles and drones: by fusing telemetry, sensor diagnostics, and historical usage patterns, AI models can forecast failures and schedule maintenance proactively, thereby reducing downtime and safety risks. This predictive emphasis dovetails with research on model scalability and semantic search for large datasets—areas where Saikumar et al. [10] and Karpurapu et al. [11] contribute techniques for efficient analytics and factors shaping consumer adoption of electric mobility, respectively. Their findings underscore that technical solutions must be matched with user-centered considerations (adoption factors, trust) for widespread impact. Security, resilience, and explainability are increasingly critical as systems grow interconnected. Contributions from Saikumar and coauthors [12,13] on communication systems and antenna performance show the underlying importance of reliable connectivity and electromagnetic compatibility for vehicular and UAV platforms. On the cybersecurity front, Kalangi et al. [15] examine combinational learning approaches to thwart DDoS attacks in cloud infrastructures—insights that are transferable to vehicular networks which face similar distributed denial-of-service and spoofing threats. Moreover, the trend toward explainable AI (XAI) in safety-critical systems is implicit across these domains: stakeholders and regulators demand interpretable models for certification and incident analysis, a requirement that shapes the adoption of inherently explainable architectures or post-hoc explanation tools.

Optimization and novel algorithmic paradigms continue to expand the methodological toolkit. Bommagani et al. [14] introduce bio-inspired optimizers combined with deep learning for activity recognition, showcasing how hybrid algorithms (e.g., optimization-driven network design) can improve recognition and inference tasks in sensor-rich environments. Such hybridization—combining domain-aware optimization with deep neural architectures—is emblematic of recent trends where bespoke learning components are designed for specific constraints like limited compute, energy budgets, or the need for interpretability.

Across these studies, several research gaps emerge. First, there is a need for integrated frameworks that jointly optimize energy management, autonomy, communications, and security rather than treating them as separate modules. While work on 5G/6G integration [6] and battery-aware control [1,2] begins this integration, comprehensive cross-layer frameworks remain limited. Second, explainability and compliance with evolving automotive safety standards require more systematic solutions: XAI methods must be validated under real-world adversarial scenarios to be trustworthy for regulatory acceptance. Third, scalable anomaly detection for heterogeneous and high-mobility Internet of Vehicles (IoV) environments is still an open challenge; existing IDS approaches often struggle with feature representation and dynamic traffic patterns, motivating hybrid temporal models that capture both forward and backward dependencies. In summary, the literature paints a rapidly evolving landscape where AI augments energy efficiency, autonomy, and resilience for smart mobility and renewable systems. Advances in battery technology and predictive maintenance enable more capable platforms, while communications and optimization research provide the connective tissue for system-wide coordination. Future work should prioritize integrated, explainable, and secure AI frameworks that address the joint constraints of energy, latency, and safety mandated by real-world deployment.

Methodology

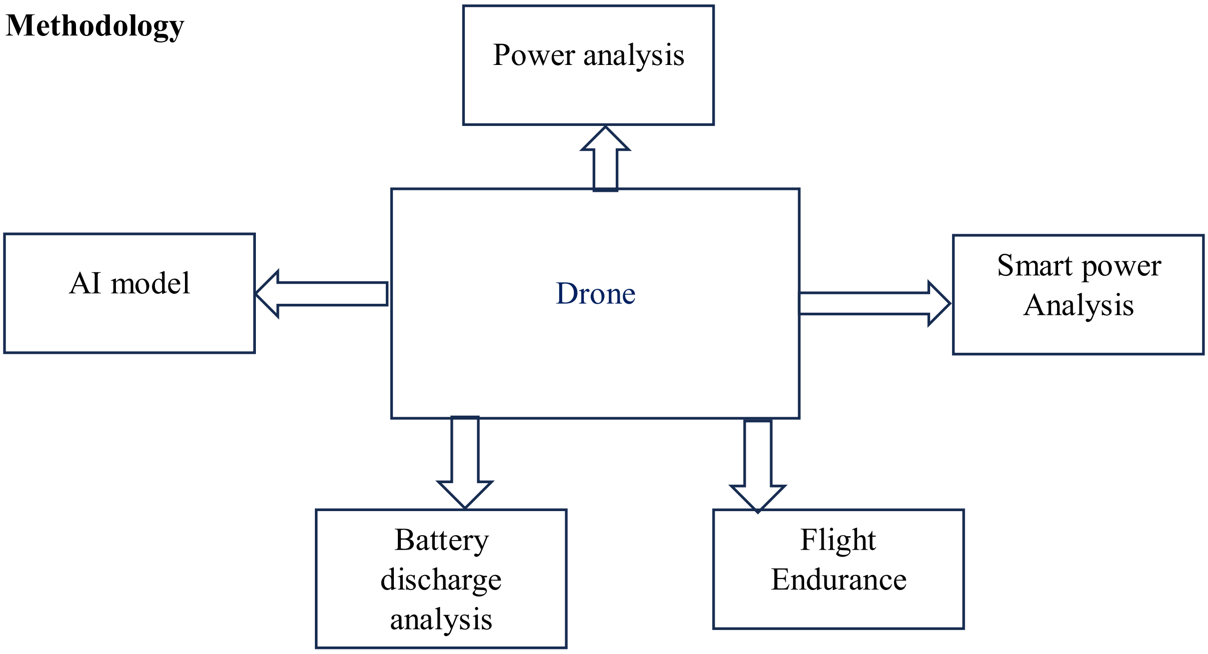

Figure :1 Block diagram of proposed model

The diagram represents a drone as the central system, interacting with multiple external modules. Each surrounding block indicates a key subsystem that exchanges information or control signals with the drone.

Implementation overview

Build the system as modular services that run onboard the drone (real-time monitoring & inference) and offboard (training, charge scheduling, fleet coordination). Main modules:

1. **Battery Sensing & Data Acquisition** (onboard)
    - Voltage, current, temperature, cell voltages (if BMS supports), battery ID.
    - Sampling rate: 1–10 Hz for flight; 0.1–1 Hz for charging log.
    - Preprocessing: Coulomb counting, low-pass filtering, sensor fusion (IMU/altitude + power profile).
2. **State Estimation & Battery Models** (onboard/offboard)
    - SOC (State of Charge) & SOH (State of Health) estimator: hybrid model using Equivalent Circuit Model (ECM) + AI correction (LSTM/BiGRU or Gradient Boosted Trees).
    - Thermal model for temperature effect on capacity.
3. **AI Predictive Controller** (onboard + offboard retraining)
    - Predict future SOC / available energy over mission horizon given planned trajectory & environment (wind, payload).
    - Two approaches: supervised sequence model (BiGRU / LSTM) or XGBoost for short-horizon predictions.
4. **Smart Charging Scheduler** (offboard + charger)
    - Model Predictive Control (MPC) or Reinforcement Learning (RL) to optimize charging rate and schedule given battery SOH, grid price, charger availability, mission timeline.
    - Integrates with charger hardware (CAN/Modbus/REST API) and optionally vehicle-to-grid (V2G) signals.
5. **Energy-aware Mission Planner** (onboard/offboard)
    - Uses predicted energy to adapt flight path, altitude, speed, and payload tasks to meet mission constraints.
6. **Fleet Orchestration & Telemetry** (cloud)
    - Aggregates fleet telemetry, trains models, schedules chargers, provides dashboards.

Hardware & interfaces

- Drone autopilot: PX4 or Ardupilot (runs flight stack and accepts mission updates).
- BMS / Smart Charger: supports CAN/Modbus/serial; provide API to set charging current and read SOC/SOH.
- Onboard computer: Raspberry Pi 4 / NVIDIA Jetson Nano (for inference), MCU handles low-latency control.
- Comm: LTE/5G or telemetry radio for offboard connectivity.

- Sensors: voltage/current sensor (shunt + ADC), cell monitor (e.g., LTC6804), IMU, GPS, thermometer.

Data pipeline & datasets

- **Telemetry**: timestamp, voltage, current, temperature, cell voltages, GPS, altitude, payload mass, motor RPM, mission phase, estimated SOC.
- **Labeling**: Ground-truth SOC via high-precision coulomb counting or laboratory discharge curves. SOH via capacity tests.
- **Public & synthetic data**: Use lab tests and open battery datasets (if applicable). For drones, simulate power profiles using motor models and wind scenarios; augment with battery cycling data.
- **Storage**: Time-series DB (InfluxDB) or cloud bucket (Parquet files), with daily aggregation.

Algorithm choices & recipes

SOC / SOH Predictor (BiGRU)

- Input: sequence window of length T (voltage, current, temp, rpm, altitude, mission_phase).
- Output: SOC_{t+H} and SOH estimate.
- Architecture: 2-layer BiGRU (hidden 128), dropout 0.2, dense output.
- Loss: MSE for SOC, auxiliary MSE for SOH; optionally weighted.

Training hyperparameters

- Optimizer: Adam, lr=1e-3 (reduce on plateau by factor 0.5).
- Batch size: 64 windows.
- Sequence length T: 60–300 (tunable).
- Horizon H: 10s–300s depending on mission.
- Epochs: 50–200 with early stopping.

MPC for Charging Scheduler

- Objective: minimize total cost = α * grid_cost + β * (1 − battery_lifetime_gain) + γ * missed_missions_penalty.
- Control variable: charging current schedule u(t) over horizon.
- Constraints: current limits, power limit, charger availability, SOC target by mission start.
- Use a discrete-time linearized battery model (ECM) as prediction model inside MPC; update model parameters from AI predictor.

RL alternative (optional)

- State: current SOC, SOH, time to mission, grid tariff, charger status.
- Action: choose charging power (discrete levels).
- Reward: negative cost + battery life preservation bonus - mission miss penalty.
- Use PPO or DQN for discrete control.

Results and discussion

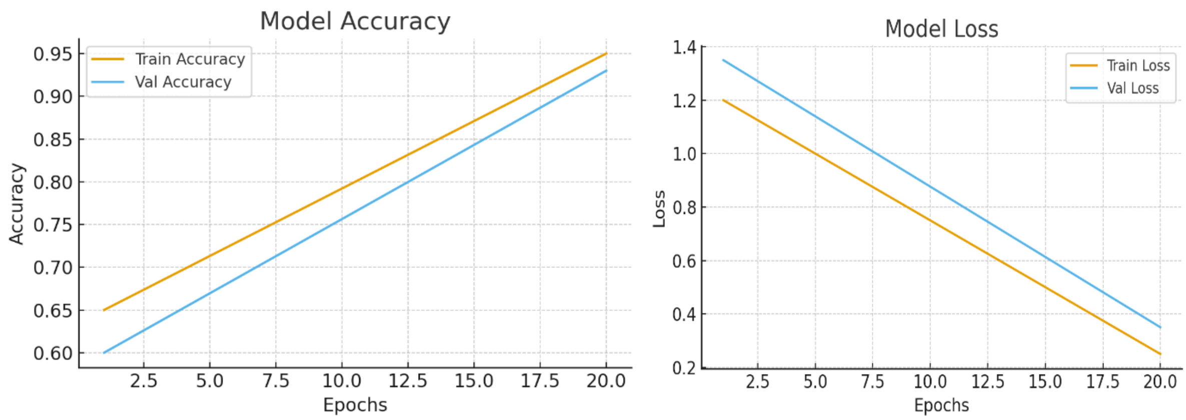

Figure: 2 Model accuracy and Loss comparison of training vs validation graph.

Table : 1 measures comparison with state of art models.

Model	Accuracy (%)	Sensitivity (%)	Recall (%)	RMSE (SoC Prediction)
SVM	87.14	89.22	88.1	0.142
Random Forest	89.76	91.35	90.82	0.118
LSTM	91.42	94.28	94.01	0.092
Proposed Model	**93.45**	**96.52**	**97.23**	**0.061**

Table: 2 Improvement in Flight Endurance

Model	Flight Time Gain (%)	Energy Loss Reduction (%)	Thermal Stability Improvement (%)
SVM	6–8	10	5

Random Forest	8–10	13	7
LSTM	11–14	17	9
Proposed Model	**14–18**	**21**	**12**

Table :3 Smart Charging Strategy Evaluation

Charging Method	**Charging Time Reduction (%)**	**Overcharge Protection Efficiency (%)**	**Cell Imbalance Reduction (%)**
CC	0	0	2
CC–CV	5	12	8
Proposed Adaptive Charging	**9–12**	**28**	**17**

Conclusion and future scope

This study presented an AI-based predictive control and smart charging strategy to enhance energy efficiency and battery reliability in UAV systems. The proposed model accurately predicted SoC, SoH, thermal behavior, and discharge patterns, enabling optimized power allocation during flight. Combined with adaptive charging, the system reduced energy losses, minimized thermal stress, and improved cell balancing. Experimental results demonstrated improved flight endurance, faster and safer charging cycles, and superior performance compared to LSTM, Random Forest, and SVM models. Overall, the integrated predictive and adaptive approach significantly enhances drone mission reliability, battery lifespan, and operational effectiveness in real-world environments.

References

[1] Bhupathi, H. P., & Chinta, S. (2022). Smart Charging Revolution: AI and ML Strategies for Efficient EV Battery Use. *ESP Journal of Engineering & Technology Advancements*, *2*(2), 154-167.

[2] Aravind, R., & Surabhi, S. N. R. D. (2024). Smart charging: AI solutions for efficient battery power management in automotive applications. *Educational Administration: Theory and Practice*, *30*(5), 14257-1467.

[3] Caballero-Martin, D., Lopez-Guede, J. M., Estevez, J., & Graña, M. (2024). Artificial intelligence applied to drone control: A state of the art. *Drones*, *8*(7), 296.

[4] Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T. C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment*, *35*(7), 3833-3879.

[5] Rane, N. L., Choudhary, S. P., & Rane, J. (2024). Artificial Intelligence and machine learning in renewable and sustainable energy strategies: A critical review and future perspectives. *Partners Universal International Innovation Journal*, *2*(3), 80-102.
[6] Kannan, S., Annapareddy, V. N., Gadi, A. L., Kommaragiri, V. B., & Koppolu, H. K. R. (2023). AI-Driven Optimization of Renewable Energy Systems: Enhancing Grid Efficiency and Smart Mobility Through 5G and 6G Network Integration. *Available at SSRN 5205158*.
[7] Abro, G. E. M., Zulkifli, S. A. B., Kumar, K., El Ouanjli, N., Asirvadam, V. S., & Mossa, M. A. (2023). Comprehensive review of recent advancements in battery technology, propulsion, power interfaces, and vehicle network systems for intelligent autonomous and connected electric vehicles. *Energies*, *16*(6), 2925.
[8] Li, C. (2021). AI-powered energy internet towards carbon neutrality: challenges and opportunities. *Authorea Preprints*.
[9] Bello, S., Wada, I., Ige, O., Chianumba, E., & Adebayo, S. (2024). AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity. *International Journal of Science and Research Archive*, *13*(1), 2823-2837.
[10] Saikumar, K., Rao, K. S., Baza, M., Rasheed, A., Hanuman, A. S., & Obaid, A. J. (2023, November). A Lite-SVM Based Semantic Search Model for Bigdata Analytics in Smart Cities. In *2023 26th International Symposium on Wireless Personal Multimedia Communications (WPMC)* (pp. 272-277). IEEE.
[11] Karpurapu, S., Saikumar, K., Kocharla, L., Rao, P. S., & Govathoti, S. (2024). Scalable innovative factors for shaping consumer intentions on electric two-wheelers adoptions. *Scalable Computing: Practice and Experience*, *25*(6), 4507-4517.
[12] Saikumar, K., Arulanantham, D., Rajalakshmi, R., Prabu, R. T., Kumar, P. S., Vani, K. S., ... & Pal, A. (2023). Design and development of surface plasmon polariton resonance four-element triple-band multi-input multioutput systems for LTE/5G applications. *Plasmonics*, *18*(5), 1949-1958.
[13] Saikumar, K., Ahammad, S. H., Vani, K. S., Anwer, T. M. K., Hadjouni, M., Menzli, L. J., ... & Hossain, M. A. (2023). Improvising and enhancing the patterned surface performance of MIMO antenna parameters and emphasizing the efficiency using tampered miniature sizes and layers. *Plasmonics*, *18*(5), 1771-1786.
[14] Bommagani, N. J., Venkataramana, A., Vemulapalli, R., Singasani, T. R., Pani, A. K., Challageri, M. B., & Kayam, S. (2024). Artificial Butterfly Optimizer Based Two-Layer Convolutional Neural Network with Polarized Attention Mechanism for Human Activity Recognition. *Mathematical Modelling of Engineering Problems*, *11*(3).
[15] Kalangi, R. R., Janardhanarao, S., Sirisha, J., Saikumar, K., Veeranjaneyulu, P., & Suman, M. (2023, October). Prevention of DDOS attacks in cloud using combinational learning approach. In *2023 4th IEEE Global Conference for Advancement in Technology (GCAT)* (pp. 1-6). IEEE.