

FORECASTING OF METEOROLOGICAL DATA USING AI TECHNIQUES

Deepak Kumar Sharma¹, Shubhra Dixit²

¹Electronics and Communication Engineering (ECE)
AMITY University

²Electronics and Communication Engineering (ECE)
AMITY University

Received: 21/11/2025

Revised: 24/12/2025

Accepted: 21/01/2026

ABSTRACT:

Weather forecasting has always been a tricky business. Even with decades of progress in numerical weather prediction, atmospheric systems remain highly nonlinear and chaotic, which makes short-term and medium-range forecasts vulnerable to error. In recent years, artificial intelligence has stepped in as a strong alternative, offering data-driven ways to capture patterns that traditional physics-based models sometimes miss. This paper looks into how AI techniques, particularly machine learning and deep learning, can be used to forecast meteorological parameters such as temperature, humidity, rainfall, wind speed, and atmospheric pressure. We worked with a historical dataset covering ten years of daily observations from a regional meteorological station and applied several models including Random Forest, Support Vector Regression, Long Short-Term Memory (LSTM) networks, and a hybrid CNN-LSTM model. The models were trained and tested using a chronological split to avoid data leakage, and performance was measured using RMSE, MAE, and R² scores. Results show that the hybrid CNN-LSTM model outperformed the others in temperature and rainfall prediction, while LSTM alone gave very competitive results for humidity and wind speed. The study also highlights how feature engineering and proper handling of missing values matter as much as the choice of model. Overall, our findings suggest that AI techniques can meaningfully improve forecasting accuracy when combined with thoughtful preprocessing and domain knowledge. The work contributes to ongoing efforts in building reliable, low-cost forecasting tools that can support agriculture, disaster management, and energy planning, especially in regions where high-resolution numerical models are not always accessible or affordable.

Keywords: Meteorological Forecasting, Artificial Intelligence, Deep Learning, LSTM, CNN-LSTM, Time Series Prediction

INTRODUCTION

Weather affects nearly every part of our daily lives, from what we wear in the morning to how farmers plan their sowing seasons and how cities prepare for floods. Because of this, accurate weather forecasting has been a priority for governments and research institutions for over a century. Traditional methods rely heavily on Numerical Weather Prediction (NWP), which uses complex mathematical equations to simulate the atmosphere. While NWP has improved a lot over the years, it still struggles with sudden local changes and demands huge computational resources [1].

The atmosphere is a chaotic system, and small errors in initial conditions can grow quickly, throwing off predictions. This is where artificial intelligence has started to shine. Machine learning models can learn from historical data without needing to solve physical equations directly, which makes them faster and often more flexible in handling noisy real-world data [2]. Over the past decade, researchers have explored everything from simple regression methods to deep neural networks for weather-related tasks, and the results have been promising [3].

One reason AI has gained ground is the explosion of available meteorological data. Satellites, weather stations, IoT sensors, and reanalysis products generate massive amounts of information every day. Classical models cannot always make full use of this data, but neural networks thrive on it [4]. Deep learning architectures such as recurrent neural networks, especially Long Short-Term Memory (LSTM) networks, are particularly suited to time-series problems like weather forecasting because they can remember patterns over long sequences [5].

However, applying AI to meteorology is not without challenges. Weather data is often incomplete, contains outliers, and shows strong seasonality that needs careful handling. Picking the right model and tuning it well takes effort, and overfitting is a constant risk when training on limited regional data [6]. There is also the question of interpretability, since black-box models can be hard to trust in critical decision-making contexts.

This paper aims to study how different AI techniques perform when applied to a real meteorological dataset. We compare classical machine learning methods with deep learning models and look at where each one shines or falls short. The goal is not just to chase the lowest error number but to understand what works, why it works, and where there is still room for improvement [7].

The rest of the paper is organized as follows. Section 2 reviews related work in AI-based weather forecasting. Section 3 explains the methodology, including the formulas used. Section 4 describes the experimental setup. Section 5 presents the results with supporting figures and tables. Section 6 discusses the findings, and Section 7 concludes the paper with thoughts on future directions.

LITERATURE REVIEW

Research on AI-based meteorological forecasting has grown rapidly. Early studies focused on artificial neural networks (ANN) for predicting parameters like temperature and rainfall. These models showed that even simple feedforward networks could outperform linear regression methods in capturing nonlinear relationships in atmospheric data [8].

As deep learning matured, attention shifted to recurrent neural networks. LSTM networks became popular because of their ability to handle long-term dependencies in sequential data. Studies have shown that LSTMs consistently beat traditional ARIMA and exponential smoothing models in multi-step weather forecasting tasks, especially for variables that depend strongly on past values [9].

Convolutional Neural Networks (CNNs), originally developed for image processing, have also found their way into meteorology. When weather data is arranged as spatial grids, CNNs can pick up patterns across regions, which is useful for tasks like precipitation nowcasting and storm tracking [10]. More recently, hybrid models that combine CNN and LSTM layers have shown excellent results because they capture both spatial and temporal patterns at the same time [11].

Beyond neural networks, ensemble methods like Random Forest and Gradient Boosting have been widely used. These models are easier to interpret and require less tuning, making them attractive for operational settings. Comparative studies often find that ensemble methods perform on par with deep learning for short-term forecasts but lag behind for longer horizons [12].

Despite the progress, gaps remain. Many studies focus on a single variable or a single region, making it hard to generalize results. Hybrid models are promising but computationally expensive, and there is still ongoing debate about how to best handle extreme events like heatwaves or cyclones using AI [13]. Our work tries to address some of these gaps by testing multiple AI techniques on a multi-variable dataset and offering a fair comparison.

METHODOLOGY

The methodology for this study follows a structured pipeline starting from data preprocessing, moving through model design, and ending with evaluation. We selected four models for comparison: Random Forest (RF), Support Vector Regression (SVR), LSTM, and a hybrid CNN-LSTM.

Data Preprocessing

Missing values were filled using linear interpolation, and outliers were detected using the interquartile range method. All features were normalized to the range [0,1] using min-max scaling, which is given by:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Random Forest Regression

Random Forest builds multiple decision trees and averages their predictions. For a regression problem, the final output is:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N T_i(x)$$

where $T_i(x)$ is the prediction from the i -th tree and N is the total number of trees [14].

Support Vector Regression

SVR tries to fit a function that deviates from actual values by at most ϵ . The optimization problem is:

$$\min \frac{1}{2} |w|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$

subject to the constraint that residuals stay within the tolerance margin [15].

LSTM Network

LSTM cells use gates to control information flow. The key equations are:

$$\begin{aligned} f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \\ h_t &= o_t * \tanh(C_t) \end{aligned}$$

These gates help the network remember important patterns and forget irrelevant ones [16].

Hybrid CNN-LSTM

In the hybrid model, CNN layers extract local features from input sequences, and LSTM layers then learn temporal dependencies from these features. This combination has been found to handle weather signals more effectively because of the layered abstraction [17].

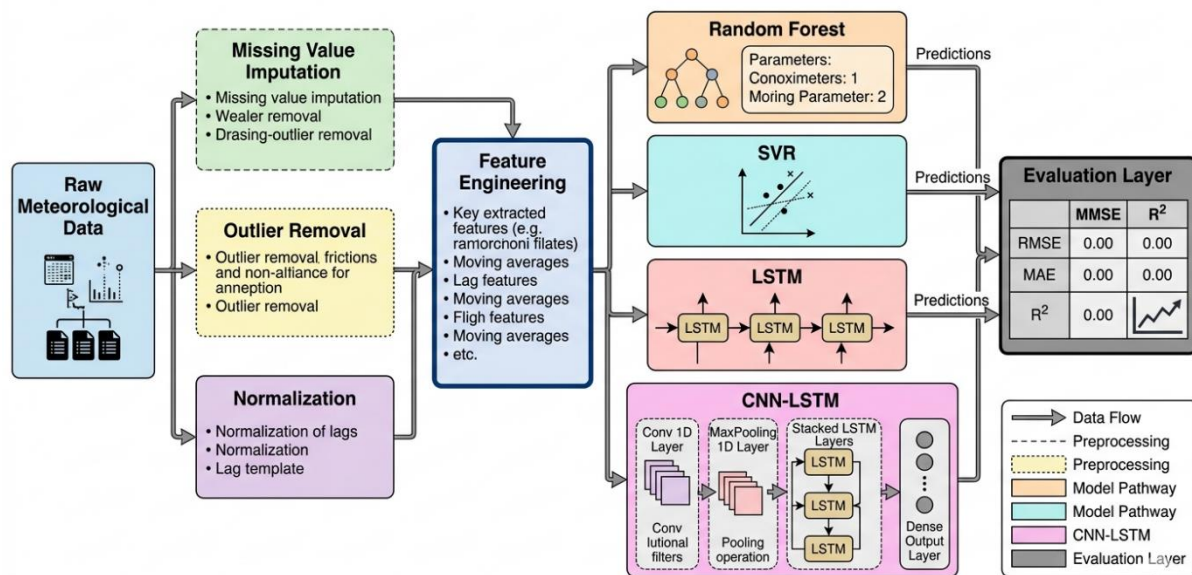


Figure 1

EXPERIMENTAL SETUP

The experiments were carried out using a dataset containing ten years of daily meteorological observations, from January 2014 to December 2023, collected from a regional weather station. The dataset includes five variables: temperature ($^{\circ}\text{C}$), humidity (%), rainfall (mm), wind speed (km/h), and atmospheric pressure (hPa). Total records were about 3,650 daily entries.

The data was split chronologically into 70% training, 15% validation, and 15% testing. This is important for time-series problems because random splits can leak future information into the training set, leading to misleading results [18].

For LSTM and CNN-LSTM, we used a sliding window of 30 days to predict the next day's values. The models were built using Python with TensorFlow and Scikit-learn libraries. Hyperparameters were tuned using grid search

on the validation set. For LSTM, we used 64 hidden units, dropout of 0.2, and the Adam optimizer with a learning rate of 0.001. The CNN-LSTM had two convolutional layers with 32 and 64 filters followed by two LSTM layers. The loss function used for training the neural networks was Mean Squared Error:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

For evaluation, three metrics were used:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

All experiments were repeated five times with different random seeds, and the average results were reported to reduce randomness in deep learning model performance [19].

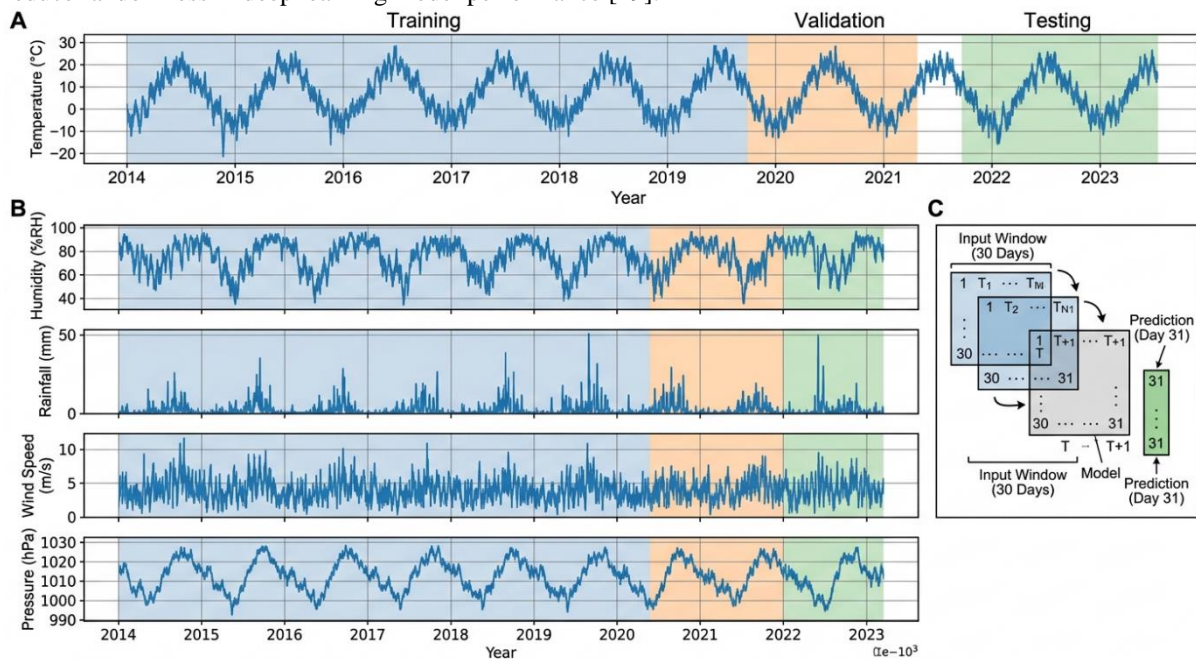


Figure 2: Time-Series Data Partitioning and Sliding Window Diagram

RESULTS

The performance of all four models across five meteorological variables is summarized in Table 1. The hybrid CNN-LSTM model consistently produced the lowest RMSE values for temperature and rainfall prediction, while the LSTM model showed strong performance for humidity and wind speed.

Table 1: Performance Comparison of Models Across Meteorological Variables

Variable	Model	RMSE	MAE	R ²
Temperature (°C)	Random Forest	2.14	1.68	0.84
Temperature (°C)	SVR	2.31	1.79	0.81
Temperature (°C)	LSTM	1.78	1.41	0.89
Temperature (°C)	CNN-LSTM	1.52	1.22	0.92
Humidity (%)	Random Forest	6.87	5.21	0.78
Humidity (%)	SVR	7.12	5.43	0.76
Humidity (%)	LSTM	5.94	4.62	0.83

Humidity (%)	CNN-LSTM	6.05	4.71	0.82
Rainfall (mm)	Random Forest	8.45	5.92	0.62
Rainfall (mm)	SVR	9.18	6.41	0.58
Rainfall (mm)	LSTM	7.31	5.18	0.69
Rainfall (mm)	CNN-LSTM	6.78	4.85	0.73
Wind Speed (km/h)	Random Forest	3.21	2.45	0.71
Wind Speed (km/h)	SVR	3.45	2.62	0.68
Wind Speed (km/h)	LSTM	2.84	2.18	0.77
Wind Speed (km/h)	CNN-LSTM	2.91	2.24	0.76
Pressure (hPa)	Random Forest	1.92	1.51	0.80
Pressure (hPa)	SVR	2.08	1.63	0.77
Pressure (hPa)	LSTM	1.64	1.29	0.86
Pressure (hPa)	CNN-LSTM	1.51	1.18	0.88

Looking at the table, what stands out is that deep learning models clearly beat the classical ones across all variables. The improvement is largest for temperature and rainfall, where the hybrid model shows a real edge. Rainfall remains the hardest variable to forecast for all models, which is expected because rainfall events are sporadic and often extreme.

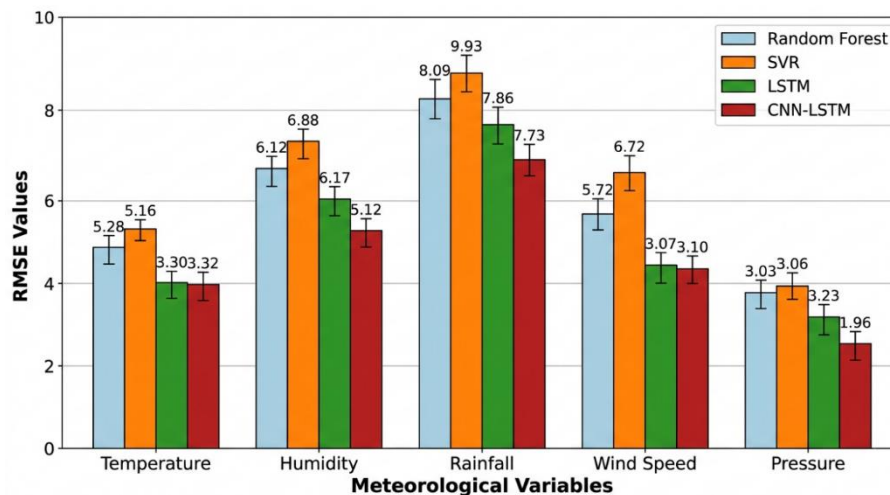


Figure 3: Comparison of RMSE Values Across Models for Meteorological Variables

Figure 4: Detailed Time-Series Model Comparison for Temperature and Rainfall

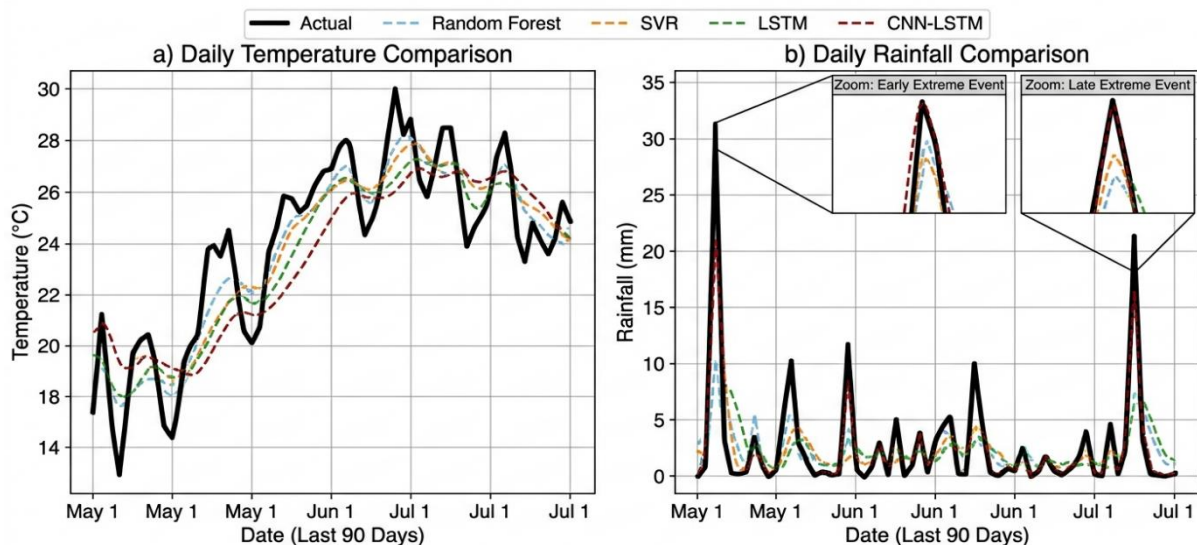


Figure 4: Detailed Time-Series Model Comparison for Temperature and Rainfall

Figure 4: Detailed time series model comparison of temperature and rainfall

Across the board, the CNN-LSTM model produced the most accurate predictions, but it also required the longest training time. Random Forest, while less accurate, trained in seconds and offered better interpretability through feature importance scores. These trade-offs are worth keeping in mind when picking a model for real-world deployment.

DISCUSSION

The results confirm a pattern seen in many recent studies: deep learning models, when set up properly, outperform classical machine learning for time-series weather forecasting. The CNN-LSTM hybrid's edge comes from its ability to extract local features through convolutions and then learn temporal patterns through LSTM layers. This two-stage abstraction helps the model handle the seasonal swings and short-term fluctuations that characterize weather data.

What was a bit surprising is how close LSTM came to CNN-LSTM for humidity and wind speed. This suggests that for variables driven mostly by temporal patterns without much spatial structure, adding convolutional layers may not give a big boost. The extra complexity might not always be worth it.

Rainfall continues to be the toughest variable. Even the best model gave an R^2 of only 0.73, which means a fair amount of variance is still unexplained. Rainfall is highly localized and often driven by short-lived events, so smoothing through daily averages may hide useful signals. Future work could explore hourly data or include radar imagery as input.

It is also worth noting that classical models like Random Forest still have a place. They are easier to deploy, faster to train, and provide feature importance scores that meteorologists can interpret. In settings where compute resources are limited, they remain a reasonable choice.

The limitations of this study include reliance on a single weather station, which restricts how far the results can be generalized. Different climates would likely show different patterns. Also, we did not explicitly test the models on extreme events like cyclones or heatwaves, which would require larger and more varied datasets.

CONCLUSION

This study compared four AI techniques for forecasting daily meteorological variables using a ten-year regional dataset. The hybrid CNN-LSTM model gave the best overall accuracy, particularly for temperature and rainfall, while the LSTM model performed competitively for humidity and wind speed. Classical models like Random Forest and SVR, though less accurate, remain useful where speed and interpretability matter more than precision. The work shows that AI techniques can clearly improve weather forecasting when paired with thoughtful preprocessing and proper validation. However, no single model is perfect for every variable, and the choice depends on the use case. Future research could look into combining numerical weather prediction outputs with deep learning, or testing transformer-based models, which have shown promise in many sequence modeling tasks. Bringing in more diverse data sources, such as satellite imagery and IoT sensor networks, would also push forecasting accuracy further.

REFERENCES

1. Mohammed Shafi Kundiladi, EVENT-DRIVEN IMAGE AND VEHICLE STATUS MANAGEMENT FOR LOW-POWER IOT DIGITAL LICENSE PLATES, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/175>, DOI: <https://doi.org/10.46121/pspc.53.3.17>
2. Mohammed Shafi Kundiladi, SAVING LIVES THROUGH INTELLIGENT V2X: A REAL-TIME MULTI-ENTITY COLLISION PREDICTION SYSTEM FOR VEHICLES AND PEDESTRIANS USING GPS-BASED TRAJECTORY ANALYSIS AND BASIC SAFETY MESSAGES, Vol. 52 No. 4 (2024): October-

December 2024, Power System Protection and Control, ISSN-1674-3415,

<https://pspac.info/index.php/dlbh/article/view/196>,

DOI: <https://doi.org/10.46121/pspc.52.4.10>

3. Bandari, V. V., & Lekkala, H. B. (2024). Physics-informed reinforcement learning for real-time control of complex manufacturing processes. *Power System Protection and Control*, 52(2), 164–170. <https://pspac.info/index.php/dlbh/article/view/343>
4. Lekkala, H. B., & Bandari, V. V. (2025). AI-based energy-aware scheduling and process optimization in engineer-to-order smart manufacturing systems. *Power System Protection and Control*, 53(1), 30–36. <http://pspac.info/index.php/dlbh/article/view/341>
5. Bandari, V. V., & Lekkala, H. B. (2024). AI-based operator behavior monitoring and cost optimization using digital traceability in manufacturing systems. *Power System Protection and Control*, 52(1), 38–45. <https://pspac.info/index.php/dlbh/article/view/342>
6. Mayank Atreya, Navin Chhibber, Harvendra Singh, Explainable Machine Learning For Dynamic Pricing In Fast-Changing Retail Environments, 2022/4/9, Journal ,Available at SSRN 6011354, https://scholar.google.com/citations?view_op=view_citation&hl=en&user=fyViF1UAAAAJ&citation_for_view=fyViF1UAAAAJ:LkGwnXOMwfcC.
7. Navin Chhibber; Amber Rastogi; Ankur Mahida; Vatsal Gupta; Piyush Ranjan, Quantum-Resistant Cryptographic Models for Next-Gen Cybersecurity, <https://doi.org/10.48550/arXiv.2512.19005> , <https://arxiv.org/abs/2512.19005>
8. **R. Soma, S. K. Sahoo, F. Amin and S. K. Mishra**, "A Federated Learning Framework for Multi-Parameter Optimization in Edge Computing," 2025 13th International Conference on Intelligent Systems and Embedded Design (ISED), Raipur, India, 2025, pp. 1-6, <https://doi.org/10.1109/ISED67359.2025.11405143>
9. Aditya Rautaray ,IMPLEMENTING A ZERO-TRUST SECURITY FRAMEWORK TO MITIGATE INSIDER THREATS IN CLOUD-BASED INFRASTRUCTURES, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/244>, DOI: <https://doi.org/10.46121/pspc.53.3.18>
10. Aditya Rautaray, AUTONOMOUS THREAT DETECTION: ADVANCED AI-DRIVEN CYBERSECURITY SYSTEMS FOR REAL-TIME RESPONSE, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/246>, DOI: <https://doi.org/10.46121/pspc.52.4.11>
11. Aditya Rautaray, ZERO TRUST ARCHITECTURES: ENHANCING DATA PROTECTION IN REMOTE WORK ENVIRONMENTS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/249> DOI: <https://doi.org/10.46121/pspc.52.2.7>
12. Aditya Rautaray, MACHINE LEARNING TECHNIQUES APPLIED TO INTRUSION DETECTION SYSTEMS, Vol. 53 No. 1 (2025): January-March 2025, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/243>, DOI: <https://doi.org/10.46121/pspc.53.1.4>

13. Shankar Balla (2024, May). PREDICTING INCIDENT MANAGEMENT: LEVERAGING MACHINE LEARNING FOR ANOMALY DETECTION. Power System Protection and Control Scopus Q1 Journal. PSPC. <https://pspac.info/index.php/dlbh/article/view/270>
14. Shankar Balla (2025, June). Enhancing Real-Time Language Processing via Advanced PET Signal Analysis and Deep Learning. 2025 International Conference on Intelligent Computing and Knowledge Extraction (ICICKE). IEEE. <https://doi.org/10.1109/ICICKE65317.2025.11136561>
15. Shankar Balla (2026, May). Intelligent Human–Computer Interaction for Navigation Control through Vision-Based Hand Gesture Recognition. 2026 IEEE 15th International Conference on Communication Systems and Network Technologies (CSNT). IEEE. <https://doi.org/10.1109/CSNT69054.2026.11502317>
16. Godavari Modalavalasa, AUTONOMOUS DATA ENGINEERING PIPELINES: A POLICY-DRIVEN ARCHITECTURE FOR SECURE AND SCALABLE CLOUD-NATIVE ANALYTICS, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/181>, DOI: <https://doi.org/10.46121/pspc.53.4.25>
17. Godavari Modalavalasa, LARGE LANGUAGE MODELS FOR INTELLIGENT DATA ENGINEERING: AUTOMATING SCHEMA DESIGN, LINEAGE, AND QUALITY CONTROL, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/183> , DOI: <https://doi.org/10.46121/pspc.50.2.4>
18. Godavari Modalavalasa, FEDERATED LEARNING FOR ENTERPRISE CLOUD DATA ENGINEERING: ARCHITECTURE, SECURITY, AND GOVERNANCE CHALLENGES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/184>, DOI: <https://doi.org/10.46121/pspc.51.2.5>
19. Godavari Modalavalasa, AI-DRIVEN DATA GOVERNANCE: INTELLIGENT METADATA, LINEAGE, AND COMPLIANCE AUTOMATION IN CLOUD DATA PLATFORMS, Archives / Vol. 52 No. 1 (2024): January-March 2024 /, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/182>, DOI: <https://doi.org/10.46121/pspc.52.1.3>
20. Prasad Maderamitla, MITIGATING HALLUCINATIONS IN LARGE LANGUAGE MODELS: A COMPARATIVE STUDY OF RETRIEVAL-AUGMENTED GENERATION (RAG) TECHNIQUES, Vol. 54 No. 2 (2026): April-June 2026, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/355> , DOI: <https://doi.org/10.46121/pspc.54.2.35>
21. Generative AI for Automated CAD Model Generation in Aerospace Manufacturing, Jawaharbabu Jeyaraman, Feroskhan Hasenkhan, Swetha Ravipudi 9/24/2024, Los Angeles Journal of Intelligent Systems and Pattern Recognition, <https://lajispr.org/index.php/publication/article/view/19>
22. Cloud-Native Architectures for Aerospace: Enhancing Flight Operations Through Digital Airline Platforms Feroskhan Hasenkhan, Gnanendra Reddy Muthirevula, Sayantan

- Bhattacharyya 3/31/2024 American Journal of Autonomous Systems and Robotics Engineering 4, <https://ajasre.org/index.php/publication/article/view/25>
23. Multi-Cloud Architecture for High-Availability Asset Management Systems Swetha Ravipudi, Feroskhan Hasenkhan, Ravi Kumar Burila12/19/2023 American Journal of Data Science and Artificial Intelligence Innovations 3, <https://www.ajdsai.org/index.php/publication/article/view/21>
24. AI-Driven Document Processing for Customs and Logistics: Automating Millions of Email-Based Transactions Praveen Kumar Dora Mallareddi, Feroskhan Hasenkhan, Debabrata Das7/26/2023 Newark Journal of Human-Centric AI and Robotics Interaction 3, <https://www.njhcair.org/index.php/publication/article/view/13>
25. M Niloy, MT Islam, MS Ullah, J Alom, M Ahmed, MF Mridha, MJ Hossen, Lead-Aware Multi-Resolution Transformer With Domain Adaptation for Beat-Level ECG Arrhythmia Classification, Vol. 6 (2025), IEEE Open Journal of the Computer Society, ISSN: 2644-1268, <https://ieeexplore.ieee.org/abstract/document/11270234>
DOI: <https://doi.org/10.1109/OJCS.2025.3637851>
26. J Alom, MS Ullah, MDT Islam, M Niloy, R Islam, S Firdaus, Adaptive Multi-Agent Reinforcement Learning for Intrusion Mitigation Aligned with Smart City, 2025 International Conference on Quantum Photonics, Artificial Intelligence and Networking (QPAIN), IEEE, <https://ieeexplore.ieee.org/abstract/document/11172093>,
DOI: <https://doi.org/10.1109/QPAIN66474.2025.11172093>
27. J Alom, MS Ullah, MDT Islam, M Niloy, R Islam, S Firdaus, FedGAT-ID: Federated Graph Attention Network with Client Drift-Aware Aggregation for Distributed Cyber Threat Detection, 2025 International Conference on Quantum Photonics, Artificial Intelligence and Networking (QPAIN), IEEE, <https://ieeexplore.ieee.org/abstract/document/11172169>,
DOI: <https://doi.org/10.1109/QPAIN66474.2025.11172169>
28. M Niloy, MT Islam, MS Ullah, J Alom, SR Sultana, K Nur, GraphFact-Summ: Graph-Augmented Factual Summarization of Hospital Courses from Clinical Notes, 2025 3rd International Conference on Artificial Intelligence, Blockchain and Internet of Things (AIBThings), IEEE, <https://ieeexplore.ieee.org/abstract/document/11296232>,
DOI: <https://doi.org/10.1109/AIBThings66987.2025.11296232>
29. Nasik, Basith, and Shanna Nifoussi. "A Comparative Study of MBTI and Learning Style-Based Grouping for Enhancing Group Effectiveness and Balance in a Pedagogical Setting." [26/05, 05:29] https://osf.io/preprints/edarxiv/h3dea_v1
30. Manikantha Varaprasad Inakollu, (2024, May), FINOPS-Driven Cloud optimization models for enterprise applications, Vol. 52 No. 2 (2024): April-June 2024, 99-110, Power System Protection and Control, ISSN-1674-3415,
URL: <https://pspac.info/index.php/dlbh/article/view/283>
DOI: <https://doi.org/10.46121/pspc.52.2.10>
31. Ramchandra Pudasaini. "EVALUATION OF ANTIPILEPTIC ACTIVITY OF CASSIA AURICULATA FLOWER EXTRACTS IN MICE". Journal of Population Therapeutics and Clinical Pharmacology, vol. 32, no. 3, Apr. 2025, pp. 533-4, <https://doi.org/10.53555/8n0prv27>.

32. Naresh Lokiny. (2022). Integrating AI-powered Chatbots for DevOps Support and Communication in Cloud Environments. *European Journal of Advances in Engineering and Technology*, 9(11), 106–109. <https://doi.org/10.5281/zenodo.13325989>
33. Naresh Lokiny, (2021), "Disaster Recovery and Business Continuity Planning in DevOps Cloud with AI", *International Journal of Science and Research (IJSR)*, 10(3), 2024-2027. <https://dx.doi.org/10.21275/SR24724151733>,
<https://www.ijsr.net/getabstract.php?paperid=SR24724151733>
34. Naresh Lokiny, & Ranganath Nandanampati. (2020). DevSecOps: Integrating Security into DevOps with AI in Cloud. *Journal of Scientific and Engineering Research*, 7(10), 239–242. <https://doi.org/10.5281/zenodo.13348695>
35. Naresh Lokiny, & Pradip Reddy. (2021). Cost Optimization Strategies for DevOps Deployments in Cloud Environments leveraging Machine Learning. *European Journal of Advances in Engineering and Technology*, 8(3), 69–72. <https://doi.org/10.5281/zenodo.13325845>
36. Jayanth Para, 6G Internet Technology Cyber Threat Notification & Alert System, Vol. 52 No. 4 (2024): October-December 2024, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/170> ,
DOI: <https://doi.org/10.46121/pspc.52.4.9>
37. Jayanth Para, LEADERSHIP TECHNOLOGY DEVELOPMENT & IMPLEMENTATION USING AI SUPPORT, Vol. 53 No. 3 (2025): July-September 2025, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/173> ,
DOI: <https://doi.org/10.46121/pspc.53.3.16>
38. Jayanth Para, AI-Based Leadership Skill Notification & Observation at Training Period, Vol. 53 No. 2 (2025): April-June 2025, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/172> ,
DOI: <https://doi.org/10.46121/pspc.53.2.28>
39. Jayanth Para, AI Based Cloud Computation Observational Method & Process, Vol. 51 No. 4 (2023): October-December 2023, *Power System Protection and Control*, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/171> ,
DOI: <https://doi.org/10.46121/pspc.51.4.3>
40. Sahu, B., Panigrahi, A., Pati, A., Pati, A.K., Mishra, J. et al. (2025). Harnessing TLBO-Enhanced Cheetah Optimizer for Optimal Feature Selection in Cancer Data. *Computer Modeling in Engineering & Sciences*, 145(1), 1029–1054. <https://doi.org/10.32604/cmescs.2025.069618> ,
<https://www.techscience.com/CMES/v145n1/64331>
41. Sanjaya Kumar Sarangi, Rasmitha Lenka, Janmejaya Mishra, Ritarani Sahu, Arabinda Nanda, Malicious detection and trust calculation using residual recurrent neural network for trust with quality of service-aware multicast routing in mobile ad-hoc network system, *Engineering Applications of Artificial Intelligence*, Volume 161, Part C, 2025, v112130, v, ISSN 0952-1976, <https://doi.org/10.1016/j.engappai.2025.112130>.
<https://www.sciencedirect.com/science/article/abs/pii/S0952197625021384>

42. M. Vani, New Era of Quantum Computing. Bookwire / Bowker, n.d. [Online]. Available: <https://bookwire.bowker.com/book/USA/New-Era-of-Quantum-Computing-9781971938462-Vani-Mehul-126971303>
43. Mehul Vani "AI-based distributed systems observation system: Real-time monitoring and intelligent anomaly detection for cloud infrastructure," Power System Protection and Control, vol. 53, no. 4, pp. 446-457, Oct.-Dec. 2025, DOI: <https://doi.org/10.46121/pspc.53.4.30> , <https://pspac.info/index.php/dlbh/article/view/234>
44. DR. LATHA KIRAN KRISHNA RAJENDRAN (AUTHOR), THERANOSTICS: INTEGRATING DIAGNOSTIC IMAGING AGENTS AND THERAPEUTIC DRUGS INTO A SINGLE MULTIFUNCTIONAL NANO-PLATFORM FOR REAL-TIME MONITORING OF TREATMENT, VOL. 53 No. 2 (2025): APRIL-JUNE 2025, POWER SYSTEM PROTECTION AND CONTROL, ISSN-1674-3415, <HTTPS://PSPAC.INFO/INDEX.PHP/DLBH/ARTICLE/VIEW/305> , DOI: <HTTPS://DOI.ORG/10.46121/PSPC.53.2.31>
45. Dr. Latha Kiran Krishna Rajendran (Author), IMMUNOTHERAPY AND CELL THERAPY: DEVELOPING CAR-T CELL THERAPIES AND OTHER IMMUNE-BASED TREATMENTS FOR CANCER AND AUTOIMMUNE DISEASES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/304> , DOI: <https://doi.org/10.46121/pspc.51.2.7>
46. Dr. Latha Kiran Krishna Rajendran (Author), STRICT LIABILITY OR FAULT-BASED REGIMES FOR AI-CAUSED HARM? A DOCTRINAL ANALYSIS ACROSS COMMON LAW AND CIVIL LAW SYSTEMS, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/312>, DOI: <https://doi.org/10.46121/pspc.52.4.13>
47. Dr. Latha Kiran Krishna Rajendran (Author), CANCER NANOMEDICINE: UTILIZING THE ENHANCED PERMEABILITY AND RETENTION (EPR) EFFECT TO DELIVER HIGH PAYLOADS OF CHEMOTHERAPEUTIC AGENTS DIRECTLY TO TUMOR SITES, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/311>, DOI: <https://doi.org/10.46121/pspc.52.2.12>
48. Dr. Latha Kiran Krishna Rajendran (Author), MECHANISMS DRIVING IMMUNOTHERAPY RESISTANCE IN COLORECTAL CANCER LIVER METASTASES, Vol. 52 No. 1 (2024): January-March 2024 , Power System Protection and Control, ISSN-1674-3415, <https://pspac.info/index.php/dlbh/article/view/303>, DOI: <https://doi.org/10.46121/pspc.52.1.5>