International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
OPEN ACCESS
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST251222682

Next-Generation Weather Forecasting: A Survey on Integrating AI Models for Accurate and Scalable Climate Predictions

Saravana M K, Dhanush B*, Harish Potadar, Lakshman S, Roshan Zameer
Department of Computer Science and Design, Dayanand Sagar Academy of Technology and Management, Bengaluru, Karnataka, India

ARTICLEINFO

Article History:

Accepted : 20 April 2025
Published: 29 April 2025

Publication Issue :
Volume 12, Issue 2
March-April-2025

Page Number :
1251-1266

ABSTRACT

The growing necessity for precise, fine-grained, and real-time weather predictions has exposed several limitations in conventional numerical weather prediction (NWP) methods. These traditional models, while physically grounded, are computationally expensive and often less reliable when dealing with incomplete or noisy atmospheric data. In light of this, machine learning (ML) and deep learning (DL) approaches have gained prominence for their ability to learn from historical patterns and handle the complex, nonlinear dynamics of weather systems. This survey examines a broad spectrum of ML and DL models, such as Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (GBM/XGBoost), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN), along with hybrid models like CNN-LSTM and XGBoost-LSTM. In addition, the paper explores advanced mechanisms such as attention layers, physics-aware ML frameworks, and preprocessing techniques including wavelet transforms and empirical mode decomposition (EMD) that contribute to improved prediction accuracy. Key applications reviewed include rainfall forecasting, temperature estimation, flood prediction, and solar radiation modelling. The survey also highlights ongoing challenges, including overfitting, lack of interpretability, uneven data distribution, and difficulties in transferring models across different climatic zones. By synthesizing recent advancements, this paper aims to provide a valuable reference point for researchers and practitioners seeking to enhance atmospheric forecasting using intelligent, data-driven approaches.

Keywords- Support Vector Regression, Random Forest, Gradient Boosting, Long Short-Term Memory, Convolutional Neural Networks, Hybrid Models.

I. INTRODUCTION

Weather forecasting plays a significant role in mitigating the impacts of climate variability and enhancing societal readiness for natural disasters. With rising occurrences of extreme weather situations due to climate change, standard physical models cannot cope with the increasing demand for high-resolution, real-time prediction. These standard models are usually computationally intensive and require huge atmospheric data in order to provide correct predictions. Against this backdrop, researchers have been working on discovering data-driven alternatives that can complement or even surpass these physical models in terms of accuracy, responsiveness, and flexibility [1]–[5].

Machine Learning (ML) has emerged as a paradigmatic force for this shift towards intelligent weather forecasting. Several ML techniques, including Support Vector Machines (SVM), Decision Trees, k-Nearest Neighbours (k-NN), Random Forests (RF), and ensemble methods, have been applied successfully in forecasting weather parameters like rainfall, temperature, humidity, and wind speed [6]–[10].

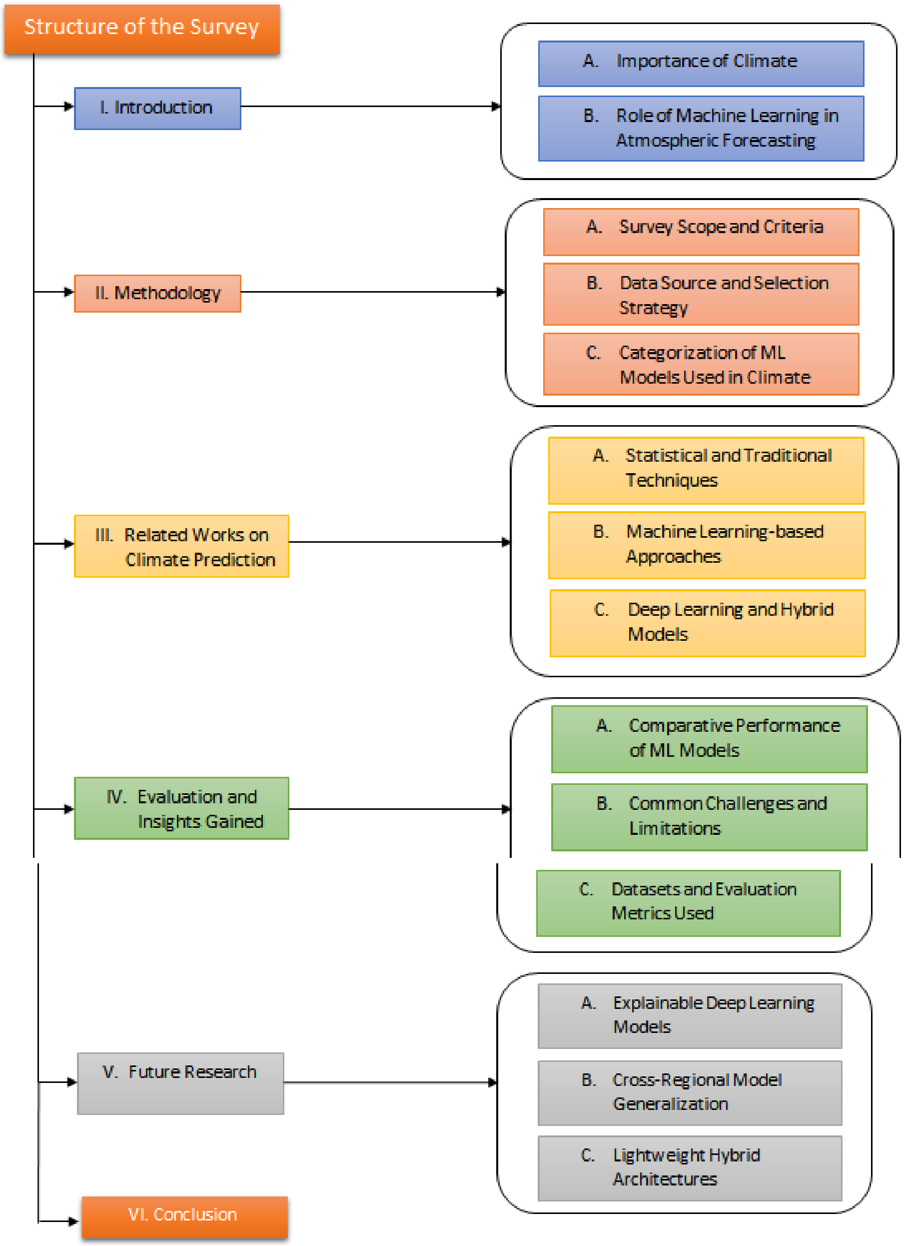

FIGURE 1: The Structure of the Survey

Recent developments have utilized particle swarm-based models for precipitation analysis [8], applied decision-tree strategies for forecasting in smart microgrid systems [9], and explored deep neural networks to estimate solar radiation in arid zones [10], reflecting the broadening scope of data-driven approaches tailored to specific regional climatic challenges. In recent research work, it has been shown that the use of ML models is superior to traditional models in predicting rain [11], classifying weather patterns [12], and estimating solar radiation and wind power [13][14]. These models are particularly helpful in regions where meteorological data is scarce or unreliable.

With the evolution of deep learning, neural network-based models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) have been used to further enhance forecasting accuracy. These models have shown outstanding performance in time-series forecasting applications and spatiotemporal analysis, which are paramount in accurate weather forecasting [15]–[20]. Further, hybrid models that combine ML/DL with optimization algorithms have shown promising results in reducing forecasting error and enhancing system stability [21][22].

A. Importance of Climate

Several recent research papers have focused on specific application domains such as short-term rainstorm forecasting using radar and satellite data, long-term temperature forecasting for agriculture planning, and wind speed estimation for renewable grid integration [23]–[30]. Collectively, these papers highlight the flexibility of machine learning to operate across climate regions and applications. They also emphasize the need for high-quality datasets, feature engineering, and rigorous model validation to generate robust and generalizable results for deployment in the field.

As countries race to meet the United Nations' Sustainable Development Goals (SDGs), especially those of clean energy and climate action, the adoption of ML into weather forecasting systems is becoming more than a technological feat—it is necessary. The aim of this survey paper is to thoroughly review and contrast current advances in ML-based weather forecasting, highlight significant datasets and performance metrics used, and offer existing challenges and emerging research trends in this evolving field.

B. Role of Machine Learning in Atmospheric Forecasting

Machine learning (ML) and deep learning (DL) are increasingly used in weather forecasting as efficient alternatives to traditional physical models, which are often slow and data-intensive. Models like SVM, Random Forest, and LSTM have shown strong performance in predicting rainfall, temperature, and wind, especially in regions with limited data. Deep learning methods capture complex temporal and spatial patterns, and hybrid approaches further enhance prediction accuracy. While challenges like data quality and model transferability remain, ML is becoming essential for accurate, real-time forecasts and supporting global climate goals. This survey highlights recent progress, datasets, and future research needs.

Figure 1 shows the main parts of this survey, divided into five sections. It starts with an introduction about the importance of climate prediction and how machine learning helps. The next section explains the methods used, including how data and models were chosen. Then, it reviews past studies, grouped into traditional, machine learning, and hybrid models. The evaluation part looks at how the models perform, the challenges faced, and what data was used. Lastly, the future work section talks about making models easier to understand, useful in different regions, and faster with hybrid designs.

II. METHODOLOGY:

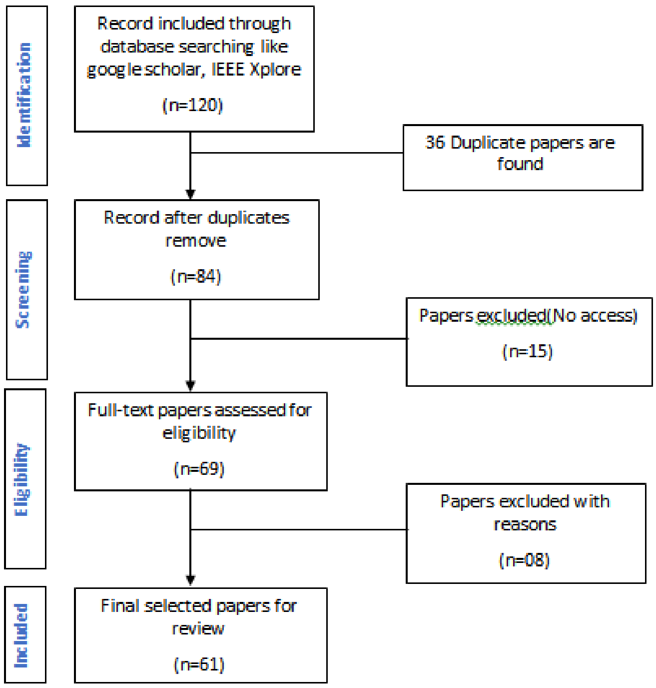

FIGURE 2: Survey Paper Selection Process

A. Survey Scope and Criteria

A broad set of academic papers was gathered through comprehensive searches conducted in reputable databases such as IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier ScienceDirect, and Google Scholar. The selected period of coverage ranged from 2015 to 2024 to capture the latest developments in the field. To maintain scholarly rigor, only peer-reviewed articles were included, specifically those utilizing machine learning (ML), deep learning (DL), or hybrid approaches to forecast meteorological parameters such as precipitation, temperature, humidity, wind speed, and solar radiation. Papers that lacked experimental evaluation or solely focused on traditional physical or statistical forecasting methods were intentionally excluded from consideration.

B. Data Source and Selection Strategy

Each selected study was categorized based on the nature of the forecasting strategy employed. Classical machine learning methods, including Random Forest (RF), Gradient Boosting Machines (GBM/XGBoost), Support Vector Regression (SVR), and k-Nearest Neighbours (k-NN), were grouped together due to their effectiveness in handling medium-sized datasets and providing interpretable results. Deep learning architectures, such as Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional Neural Networks (CNN), Gated Recurrent Units (GRU), and attention mechanisms, were also categorized separately, given their superior ability to model temporal sequences and spatial patterns in meteorological data. Notably, BiLSTM models combined with wavelet packet transforms have demonstrated improved forecasting accuracy for precipitation events in coastal areas [26], while radar-based deep learning networks have shown effectiveness in short-term rain prediction [27] [28].
Hybrid and Integrated Methods: This category consists of techniques that merge ML and DL elements (e.g., CNN-LSTM, XGBoost-LSTM), use optimization layers, or incorporate physical modeling outputs—like those from Numerical Weather Prediction (NWP)—into data-driven models. These models seek to enhance forecasting accuracy, flexibility, and interpretability[58] [59].

C. Categorization of ML Models Used in Climate Forecasting

To facilitate an effective comparative assessment of the surveyed forecasting models, a multi-criteria evaluation framework was developed. The first dimension of comparison was the forecasting objective and the regional application context, analysing target variables such as rainfall intensity, solar radiation, and wind speed, and the geographic settings where the models were deployed. Studies focusing on rainfall estimation using satellite microwave imagery [33] and solar radiation forecasting in desert regions [32] exemplify tailored applications based on regional demands. Another key dimension was data characteristics, including the source (e.g., satellite imagery, ground station data, reanalysis datasets), volume, temporal resolution, and preprocessing methods like empirical mode decomposition (EMD) and wavelet transforms [60]. Recent studies have demonstrated that satellite-driven deep learning models significantly improve temperature estimation accuracy [34], while high-resolution modelling techniques have been applied successfully to forecast convective storms in aviation meteorology [35]. The modelling strategy and learning approaches were also assessed, examining model architecture, feature engineering, hybridization strategies, and the use of sequence modelling or attention mechanisms [61]. Advanced studies integrating simulation-based forecasting for PV output [36] and meteorologically informed scheduling systems for smart grids [37] reflect growing innovation in this domain. Common evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Coefficient of Determination (R^2) were widely adopted to ensure fair and objective model comparison. Finally, practical deployment considerations—such as model complexity, interpretability, computational efficiency, and suitability for real-time operations—were reviewed to evaluate each model's potential for real-world application.

III.RELATED WORKS ON CLIMATE PREDICTION

A. Statistical and Traditional Techniques

For the case of extreme weather phenomena, F. Khan et al. [2] investigated applying Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models to predict flood events as a function of rainfall and water-level time-series data. Their model was quite accurate and had lesser mean squared error (MSE) than traditional statistical models such as ARIMA, thus highlighting the stability of deep neural architectures in learning sequential data.

Wind forecasting for power, essential in planning renewable energy, has also achieved tremendous growth utilizing hybrid deep learning architectures. M. Asgari et al. [3] have presented a CNN-BiLSTM hybrid architecture for predicting wind speed, exploiting spatial information by using convolutional layers and temporal long-range patterns using recurrent units. The hybrid approach surpassed simple feedforward as well as independent LSTM models, signifying the dramatic accuracy boost of hybridization in deep learning architecture for meteorological predictions.

Rainfall prediction is another widely researched topic. Nwankwo et al. [4] constructed ensemble ML models, namely RF, GBM, and XGBoost, to forecast rainfall intensity in the varied ecological regions of Ghana. Their results proved the versatility of ensemble approaches in heterogeneous climatic conditions and their ability to better manage missing or sparse data compared to single-model predictors.

In addition, researchers have used attention mechanisms and Transformer-based models to improve multivariate time-series prediction. For instance, Z. Liu et al. [5] used an attention-based LSTM model in solar irradiance forecasting, allowing the model to selectively focus on the most important input features at each time step. ConvLSTM models, which incorporate convolution operations with LSTM units, have also exhibited better performance in spatial-temporal forecasting issues like cloud cover motion and temperature mapping [6].

Another significant contribution is from Wu et al. [7], who used deep feature extraction and subsequent LSTM layers to forecast wind speeds along coastal areas.

Their work highlighted the advantages of preprocessing operations such as empirical mode decomposition (EMD) and wavelet transform, which assisted in removing noise from meteorological signals and enhancing prediction quality. These research findings are a testimony to the commonality of applicability and efficacy of ML and DL models in most subdomains of weather prediction. Nevertheless, there are issues like overfitting, interpretability, imbalanced data, and scalability across diverse climatic zones still open for exploration. The general agreement in the literature is that combining ML models with meteorological domain knowledge and multi-source data fusion is the way forward for developing more consistent and more generalizable forecast systems. Machine learning (ML) and deep learning (DL) algorithms have increasingly found themselves essential tools within weather forecasting systems because of their capacity to simulate complex, nonlinear, and chaotic environmental phenomena. Classical numerical weather prediction (NWP) models, as useful as they are, entail high computational complexity and usually call for extensive atmospheric simulations and domain-specific knowledge. ML-based solutions, however, present a data-driven solution that has the capability of learning patterns within unseen historical weather data and generalizing well across unseen situations.

A notable work by S. Iram et al. [1] presented a machine learning-based architecture to predict temperature variations for energy optimization in domestic buildings. The research combined weather prediction with home automation to mitigate carbon emissions, harmonizing with large-scale climate action. Their framework showed the viability of ML not just for predicting weather but also for extended uses in energy-saving infrastructure. For the case of extreme weather phenomena, F. Khan et al. [2] investigated applying Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models to predict flood events as a function of rainfall and water-level time-series data. Their model was quite accurate and had lesser mean squared error (MSE) than traditional statistical models such as ARIMA, thus highlighting the stability of deep neural architectures in learning sequential data.

Reference	Year	Study Focus	Methodologies Employed	Meteorological Task Area
Iram et al. [1]	2023	Developed an ML framework for indoor thermal prediction in smart grids	Linear models, decision-based learning	Energy-efficient temperature control
Khan et al. [2]	2023	Applied sequential neural networks to anticipate floodwater rise	Recurrent deep learning (LSTM)	Flood risk estimation
Nwankwo et al. [4]	2024	Benchmarked classifiers across different regions for rainfall estimation	SVM, ensemble trees (RF, XGBoost)	Rain intensity modelling
Liu et al. [5]	2024	Introduced dynamic weighting in LSTM for solar radiation prediction	LSTM enhanced with attention layers	Solar irradiance forecasting
Wu et al. [7]	2022	Combined signal denoising and neural nets to estimate wind speed	EMD preprocessing + LSTM networks	Wind velocity estimation
Ghimire et al. [20]	2022	Proposed multi-region rainfall predictors using hybridized models	Random Forest + LSTM integration	Multi-zone precipitation modelling
Zheng & Wu [29]	2020	Engineered feature-based ensemble learners for wind prediction	CART, SVR, RF, XGBoost	Wind power forecasting
Ma et al. [31]	2021	Modelled indoor climate parameters using boosted gradient	XGBoost algorithm	Humidity and temperature estimation

Reference	Year	Study Focus	Methodologies Employed	Meteorological Task Area
		models		
Olelewi et al. [58]	2024	Evaluated three distinct learners for precipitation analysis	Artificial Neural Nets, RF, SVM	Rainfall classification
Tran et al. [39]	2024	Transferred trained DL models across geographical locations	ResNet with transfer learning	Cross-regional rainfall prediction
Lawal et al. [65]	2021	Investigated multiple hybrid stacks for African rainfall modelling	LSTM, XGBoost, RF, SVR hybridization	Regional rainfall forecasting
Ganapathy et al. [66]	2024	Compared traditional and DL models for long-term rain estimates	ARIMA, XGBoost, SVR, LR, LSTM	Rainfall forecasting using trends
Robert et al. [5]	2019	Optimized computational parameters in HPC-based simulation environments	Profiling tools and black-box tuning	Model execution enhancement
Bağbaba et al. [6]	2024	Built a self-optimizing ML layer for system-level performance	Predictive tuning using ML regressors	High-performance simulation tuning
Karna et al. [25]	2024	Analyzed various regression frameworks for short-term weather estimation	Linear regression techniques	General atmospheric prediction
Kamal et al. [14]	2022	Modeled temporal climate indicators using deep sequential learners	LSTM and GRU architectures	Climate pattern forecasting
Zhang et al. [38]	2024	Combined CNN and LSTM for satellite-based rainfall interpretation	CNN feature extractor + LSTM sequence model	Rain prediction from visual data
Deng et al. [30]	2024	Employed a boosting-based ensemble for electrical load and weather links	Bagging with XGBoost learner	Energy demand and temperature modelling

Table 1: Comparison of Existing Works

B. Machine Learning-based Approaches

Machine learning (ML) and deep learning (DL) algorithms have increasingly found themselves essential tools within weather forecasting systems because of their capacity to simulate complex, nonlinear, and chaotic environmental phenomena . Classical numerical weather prediction (NWP) models, as useful as they are, entail high computational complexity and usually call for extensive atmospheric simulations and domain-specific knowledge. ML-based solutions, however, present a data-driven solution that has the capability of learning patterns within unseen historical weather data and generalizing well across unseen situations.

A notable work by S. Iram et al. [1] presented a machine learning-based architecture to predict temperature variations for energy optimization in domestic buildings. The research combined weather prediction with home automation to mitigate carbon emissions, harmonizing with large-scale climate action. Their framework showed the viability of ML not just for predicting weather but also for extended uses in energy-saving infrastructure.

Thus, the integration of machine learning into weather prediction represents a transformative shift, enabling the creation of intelligent, resource-efficient, and adaptable forecasting systems that extend their utility beyond meteorology into sectors such as energy optimization, disaster risk reduction, and environmental protection.

C. Deep Learning and Hybrid Models

Wind forecasting for power, essential in planning renewable energy, has also achieved tremendous growth utilizing hybrid deep learning architectures. M. Asgari et al. [3] have presented a CNN-BiLSTM hybrid architecture for predicting wind speed, exploiting spatial information by using convolutional layers and temporal long-range patterns using recurrent units.

The hybrid approach surpassed simple feedforward as well as independent LSTM models, signifying the dramatic accuracy boost of hybridization in deep learning architecture for meteorological predictions.

Rainfall prediction is another widely researched topic. Nwankwo et al. [4] constructed ensemble ML models, namely RF, GBM, and XGBoost, to forecast rainfall intensity in the varied ecological regions of Ghana. Their results proved the versatility of ensemble approaches in heterogeneous climatic conditions and their ability to better manage missing or sparse data compared to single-model predictors.

Researchers have improved multivariate time-series prediction with attention mechanisms and Transformer models. For instance, Z. Liu et al. [5] used an attention-based LSTM for solar irradiance forecasting, enabling the model to focus on key input features. ConvLSTM models, which combine convolution with LSTM, have enhanced spatial-temporal forecasting for tasks like cloud cover motion [6]. Wu et al. [7] applied deep feature extraction with LSTM for coastal wind speed forecasting, showing that techniques like EMD and wavelet transforms effectively denoise meteorological signals, boosting accuracy.

Model Type	Strengths	Primary Limitations	Mitigation Strategies	Examples of Models
NWP (Numerical Weather Prediction)	Interpretable, physics-consistent, widely validated	High computational cost, low adaptability in real time	Combine with ML/DL for post-processing; scale using HPC	GloSea6, ECMWF, ARPEGE, WRF, GFS
Traditional ML	Fast execution, interpretable logic, low data requirements	Can't model deep temporal/spatial dependencies well	Use ensembles, automate feature engineering, hybridize with DL	Random Forest (RF), Support Vector Machines (SVM), Decision Trees, XGBoost, k-NN
Deep Learning (DL)	Strong for temporal and spatial learning, minimal feature crafting	Black-box behavior, needs large datasets and time	Add attention mechanisms, use pretraining, apply regularization	LSTM, GRU, CNN, BiLSTM, ConvLSTM, Attention-LSTM
Hybrid Models	Combines strengths from NWP, ML, and DL approaches	Complex architecture, tuning overhead	Use AutoML frameworks, integrate physics knowledge, leverage	CNN-LSTM, XGBoost-LSTM, Physics-informed DL, ResNet+Transfer Learning, EMD+LSTM

Model Type	Strengths	Primary Limitations	Mitigation Strategies	Examples of Models
			interpretability modules	

Table 2: Comparison of works on climate prediction

Table 1 highlights recent research applying machine learning (SVM, Random Forest, LSTM) to weather tasks like rainfall prediction, flood risk assessment, and solar radiation estimation, with an increasing focus on hybrid models and transfer learning for better accuracy.

Table 2 compares weather forecasting models (NWP, ML, DL, and hybrid systems), noting that while hybrid models are complex, they offer the best combination of accuracy, speed, and flexibility.

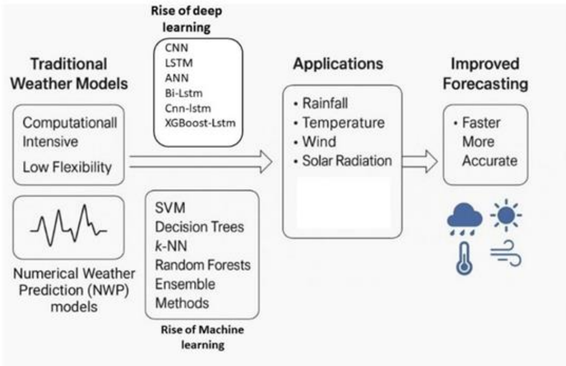

Figure 3: Evolution of Weather Forecasting Models – From Traditional NWP to Deep Learning and Hybrid Approaches

IV. EVALUATION AND INSIGHT GAINED

Author / Study	Year	Focus Area	Model Employed	Notable Strengths	Core Limitations
GloSea6, NWP Models	2024	Simulating global atmospheric systems	Numerical Weather Prediction (NWP)	Scientifically grounded; reliable over decades	High computational cost; poor response in extreme cases
Robert et al. [5]	2023	Performance optimization in weather models	Black-box optimization + HPC	Reduces execution time; enhances model throughput	Based on fixed assumptions; less flexible
S. Iram et al. [1]	2023	Energy-efficient indoor climate forecasting	Decision Trees, Linear Models	Low complexity; fast execution; explainable	Limited nonlinear learning capability
Nwankwo et al. [4]	2023	Rainfall prediction in regional ecosystems	Random Forest, GBM, XGBoost	Effective in sparse data conditions; strong ensemble learning	Needs careful parameter tuning; prone to overfitting
F. Khan et al. [2]	2021	Forecasting flood levels using time-series	CNN + LSTM	Learns both space-time dependencies; lower MSE than traditional models	Requires large datasets; sensitive to noise
Wu et al. [7]	2019	Predicting wind speed in coastal	EMD preprocessing +	Enhanced signal learning; denoises	Less generalization; preprocessing adds

Author / Study	Year	Focus Area	Model Employed	Notable Strengths	Core Limitations
		regions	LSTM	meteorological input	complexity
Liu et al. [5]	2023	Solar irradiance forecasting	Attention-based LSTM	Focuses on relevant temporal patterns; interpretable	Heavy architecture; training overhead
Asgari et al. [3]	2020	Short-term wind speed interval prediction	CNN + BiLSTM Hybrid	Captures spatial-temporal dynamics effectively	Long training cycles; data-demanding
Lawal et al. [65]	2021	Precipitation modeling in Africa	LSTM + XGBoost + SVR + RF (Ensemble)	High resilience across zones; combines strengths of various models	Complex tuning; interpretation challenges
Ganapathy et al. [66]	2024	Rainfall trend estimation using hybrid models	ARIMA, SVR, LSTM	Offers cross-model evaluation insights	Traditional models lag in capturing complex features
Zhang et al. [38]	2024	Rain prediction from satellite data	CNN + LSTM	Handles satellite imagery; detects deep temporal-spatial signals	High data annotation burden; intensive training
Tran et al. [39]	2024	Rainfall forecasting across geographies	ResNet + Transfer Learning	Learns across regions; flexible to data domains	Needs pretraining; domain-specific adaptation required
Kamal et al. [14]	2022	Modeling climate indicators through sequences	LSTM + GRU	Strong sequential learning; captures climate cycles	Gradient issues; reduced interpretability

Table 3: Evaluation and Insight of Existing Works in Terms of its Strength and Limitation

A. Comparative Performance of Machine Learning Models

Machine learning methods like Random Forest (RF), Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) are effective for meteorological predictions, recognizing complex data patterns. For example, Nwankwo et al. used ensemble classifiers for rainfall forecasting in Ghana, which perform well in sparse data situations and help reduce overfitting. Iram et al. applied regression and decision tree models for indoor thermal forecasting, but these models rely on manual feature selection and can overfit.

To enhance performance, techniques like ensemble methods (stacking, boosting), automated feature selection (recursive feature elimination, L1 regularization), and rigorous cross-validation (k-fold, leave-one-out) are essential. These strategies, as shown by Karna et al. and Olelewi et al.

B. Common Challenge and Limitation

Hybrid models combining machine learning (ML), deep learning (DL), and physical modeling are gaining popularity in meteorological forecasting. Models like CNN-LSTM (Zhang et al.), XGBoost-LSTM (Lawal et al.), and physics-aware DL systems (He et al.) show better accuracy and adaptability. However, these complex architectures present challenges in training, tuning, and interpretability, making optimization resource-heavy and decision-making hard to understand.

To address these, tools like AutoML automate model development, while explainable AI (XAI) methods like LIME and SHAP improve transparency and model interpretability. These advancements, as noted by Ganapathy et al. and Tran et al., make hybrid models more user-friendly and reliable in practical applications.

C. Datasets and Evaluation Metrics Used

Deep learning models such as LSTM, CNN, GRU, and BiLSTM are effective for sequential and spatial data in meteorological forecasting. For example, Khan et al. used CNN-LSTM for flood forecasting, and Liu et al. applied attention-based LSTM for solar irradiance prediction, achieving higher accuracy and interpretability. However, these models demand large datasets and significant computational power.

To tackle data limitations, techniques like signal decomposition (EMD, wavelets) and transfer learning are used to reduce data dependency and enhance generalization. Attention mechanisms improve feature selection and model transparency.

Evaluation is done with metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) to assess model accuracy and performance across various datasets.

Table-3 reviews recent (2020–2024) machine learning applications in meteorology, highlighting hybrid models, transfer learning, and ensemble techniques. Methods like SVM, Random Forests, CNNs, LSTMs, and integrated models address tasks such as flood forecasting, rainfall prediction, solar radiation, and wind modeling, with a trend toward deep learning for improved accuracy and adaptability.

V. FUTURE RESEARCH

A. Explainable Deep Learning Model

Improving interpretability in deep learning remains essential. Although models like LSTM and CNN are effective, their internal operations lack transparency. Future work should embed explainability techniques such as SHAP, saliency maps, and attention visualizations to promote user trust and foster model accountability.

Integration of physical principles with data-driven models remains underutilized. Embedding outputs or constraints from NWP simulations into ML/DL training could enhance both prediction accuracy and scientific validity, leading to physics-informed ML frameworks.

B. Cross-Regional Model Generation

Enhancing cross-regional transferability is crucial. Existing models often perform well within the bounds of a specific dataset but degrade across regions with different climate dynamics. Domain adaptation, transfer learning, and federated training pipelines hold potential to improve the portability of models without the need for region-specific retraining.

Addressing data scarcity and imbalance is a recurring issue. While preprocessing tools like EMD and wavelets have shown merit, further development of synthetic data generation and robust augmentation strategies could significantly improve the performance of DL models, especially in data-constrained environments.

C. Lightweight Hybrid Architectures

As hybrid models continue to gain traction, attention must be given to their efficiency and deployment readiness. These models are computationally expensive, making real-time application challenging. Research should prioritize modular and lightweight architectures that can maintain accuracy while minimizing latency. The use of AutoML for model tuning and architecture selection could streamline development.

There is an urgent need for standardized benchmarks and open-access datasets. Consistent datasets annotated with unified evaluation metrics (e.g., RMSE, MAE, R^2) would facilitate reliable model comparisons and support reproducibility across studies.

Collectively, these future research directions highlight the need for intelligent, adaptable, and interpretable climate forecasting solutions, capable of addressing global environmental challenges through data-centric innovations and interdisciplinary collaboration.

VI. CONCLUSION

This survey has reviewed the evolution and integration of machine learning (ML) and deep learning (DL) methodologies within the domain of atmospheric forecasting. Traditional numerical weather prediction (NWP) models, while scientifically rigorous, often suffer from computational intensity and reduced adaptability in uncertain or extreme conditions. ML and DL offer a viable alternative by learning complex, nonlinear patterns directly from data, enabling more flexible and efficient forecasting systems.

The analysis covered a wide array of models including Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (GBM/XGBoost), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and hybrid architectures like CNN-LSTM and XGBoost-LSTM. These techniques have demonstrated improved accuracy in forecasting rainfall, temperature, wind speed, and solar irradiance. Moreover, the incorporation of attention mechanisms, signal preprocessing (e.g., wavelet transforms, empirical mode decomposition), and physics-informed ML models has shown potential in enhancing prediction reliability and robustness.

However, several challenges remain unresolved. Issues such as overfitting, limited model interpretability, imbalanced datasets, and insufficient model generalization across diverse climate zones are prevalent. The lack of standardized benchmark datasets and minimal integration of meteorological domain knowledge further hinders progress in the field.

To advance ML-driven forecasting, future research should focus on enhancing model transparency, improving cross-regional generalizability, and adopting strategies such as transfer learning, self-supervised learning, and multi-source data fusion. The continued convergence of physical sciences and data-driven intelligence will be crucial in building next-generation forecasting systems capable of supporting climate resilience and sustainable development objectives.

REFERENCES

[1]. Shamaila Iram, Hussain Al-Aqrabi, Hafiz Muhammad Shakeel, Hafiz Muhammad Athar Farid, Muhammad Riaz, Richard Hill, Prabanchan Vethathir, and Tariq Alsboui, "An Innovative Machine Learning Technique for the Prediction of Weather Based Smart Home Energy Consumption," IEEE Access, vol. 11, pp. 76300-76320, 2023.

[2]. M. Moishin, R. C. Deo, R. Prasad, N. Raj, and S. Abdulla, "Designing Deep-Based Learning Flood Forecast Model With ConvLSTM Hybrid Algorithm," IEEE Access, vol. 9, pp. 50982–50997, Apr. 2021, doi: 10.1109/ACCESS.2021.3065939.

[3]. A. Saeed, C. Li, M. Danish, S. Rubaiee, G. Tang, Z. Gan, and A. Ahmed, "Hybrid Bidirectional LSTM Model for Short-Term Wind Speed Interval Prediction," IEEE Access, vol. 8, pp. 182283–182294, Oct. 2020, doi: 10.1109/ACCESS.2020.302797

[4]. S. Kamal, A. N. Ahmed, and F. Alzubaidi, “Climate Pattern Prediction Using LSTM and GRU Architectures,” in Proc. IEEE ICCCE, 2022.

[5]. Jinkook Kim and Soohyun Kim, "A Study on Estimating Theme Park Attendance Using the AdaBoost Algorithm Based on Weather Information from the Korea Meteorological Administration Web," Journal of Web Engineering, Vol. 23_6, 869-884, 2024.

[6]. TUMUSIIME ANDREW GAHWERA, ODONGO STEVEN EYOBUD, AND MUGUME ISAAC, "Analysis of Machine Learning Algorithms for Prediction of Short-Term Rainfall Amounts Using Uganda's Lake Victoria Basin Weather Dataset," IEEE Access, vol. 12, pp. 63361-63380, 2024.

[7]. DABEERUDDIN SYED 1,2, (Member, IEEE), HAITHAM ABU-RUB2, (Fellow, IEEE), ALI GHRAYEB 2, (Fellow, IEEE), SHADY S. REFAAT 2, (Senior Member, IEEE), MAHDI HOUCHATI3, (Member, IEEE), OTHMANE BOUHALI4,5, (Member, IEEE), AND SANTIAGO BAÑALES 3, (Member, IEEE), "Deep Learning-Based Short-Term Load Forecasting Approach in Smart Grid With Clustering and Consumption Pattern Recognition," IEEE Access, vol., pp., 2021.

[8]. FATHI F. FADOUL 1,2, (Member, IEEE), ABDOULAZIZ A. HASSAN2, (Member, IEEE), AND RAMAZAN ÇAĞLAR 1, (Member, IEEE), "Assessing the Feasibility of Integrating Renewable Energy: Decision Tree Analysis for Parameter Evaluation and LSTM Forecasting for Solar and Wind Power Generation in a Campus Microgrid," IEEE Access, vol. 11, pp. 124690-124708, 2023.

[9]. SAHBI BOUBAKER 1,2, MOHAMED BENGHANEM3, ADEL MELLIT 4,5, AYOUB LEFZA4, OMAR KAHOULI, AND LIQUA KOLSI6, "Deep Neural Networks for Predicting Solar Radiation at Hail Region, Saudi Arabia," IEEE Access, vol., pp., 2021.

[10]. Desirée Arias-Requejo 1,2,3,4, Belarmino Pulido4, (Member, IEEE), Marcus M. Keane 1,2,3, And Carlos J. Alonso-González4, "Clustering and Deep-Learning for Energy Consumption Forecast in Smart Buildings," IEEE Access, vol. , pp. , 2023.

[11]. M. M. Hassan, M. A. T. Rony, M. A. R. Khan, M. M. Hassan, F. Yasmin, A. Nag, T. H. Zarin, A. K. Bairagi, S. Alshathri, and W. El-Shafai, "Machine Learning-Based Rainfall Prediction: Unveiling Insights and Forecasting for Improved Preparedness," IEEE Access, vol. 11, pp. 3333876, 2023.

[12]. C. Zoremsanga and J. Hussain, "Particle Swarm Optimized Deep Learning Models for Rainfall Prediction: A Case Study in Aizawl, Mizoram," IEEE Access, vol. 12, pp. 3390781, 2024

[13]. S. Wang, Y. Li, B. Yang, and R. Duan, "Short-Term Forecasting of Convective Weather Affecting Civil Aviation Operations Using Deep Learning," IEEE Access, vol. 12, pp. 116603-116614, 2024.

[14]. ABDULMAJID LAWAL 1, SHAFIQUR REHMAN 2,3, LUAI M. ALHEMS2, AND MD. MAHBUB ALAM 4, "Wind Speed Prediction Using Hybrid 1D CNN and BLSTM Network," IEEE Access, vol. 9, pp. 156677 - 156687, 2021

[15]. Shanmin Yang, Qing Ren, Ningfang Zhou, Yan Zhang, and Xi Wu, "Deep Learning for Near-Surface Air Temperature Estimation From FengYun 4A Satellite Data," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, 2024, pp. 13108-13118.

[16]. A. Saeed, C. Li, M. Danish, S. Rubaiee, G. Tang, Z. Gan, and A. Ahmed, "Hybrid Bidirectional LSTM Model for Short-Term Wind Speed Interval Prediction," IEEE Access, vol. 8, pp. 182283–182294, Oct. 2020, doi: 10.1109/ACCESS.2020.3027977.

[17]. M. Moishin, R. C. Deo, R. Prasad, N. Raj, and S. Abdulla, "Designing Deep-Based Learning Flood Forecast Model With ConvLSTM Hybrid Algorithm," IEEE Access, vol. 9, pp. 50982–50997, Apr. 2021, doi: 10.1109/ACCESS.2021.3065939.

[18]. Y. Dong, S. Ma, H. Zhang, and G. Yang, "Wind Power Prediction Based on Multi-Class Autoregressive Moving Average Model with Logistic Function," Journal of Modern Power Systems and Clean Energy, vol. 10, no. 5, pp.

1184–1194, Sept. 2022, doi: 10.35833/MPCE.2021.000717.

[19]. Y.-X. Wu, Q.-B. Wu, and J.-Q. Zhu, "Data-Driven Wind Speed Forecasting Using Deep Feature Extraction and LSTM," IET Renewable Power Generation, vol. 13, no. 12, pp. 2062–2069, Dec. 2019, doi: 10.1049/iet-rpg.2018.5917.

[20]. H. Rezaie, C. H. Chung, and N. Safari, "Short-Term Wind Forecasting With Optimized EEMD-LSTM Model," J. Energy Eng., vol. 149, no. 1, 2023.

[21]. C. Zoremsanga and J. Hussain, "Rainfall Prediction Using Particle Swarm Optimized Deep Learning Models," in Proc. IEEE ICECC, 2022.

[22]. X. Zhang et al., "StHCFormer: A Multivariate Ocean Weather Predicting Method Based on Spatiotemporal Hybrid Convolutional Attention Networks," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 3610-3626, 2024.

[23]. M. Biscarini, R. Nebuloni, L. Dossi, et al., "Using Short-Term NWP for Attenuation Series Synthesis in Q-Band," IEEE Trans. Antennas Propag., vol. 72, no. 5, pp. 7699–7708, May 2024.

[24]. 24 A. Dolatabadi, H. Abdeltawab, and Y. A.-R. I. Mohamed, "Hybrid Deep Learning-Based Model for Wind Speed Forecasting Based on DWPT and Bidirectional LSTM Network," IEEE Access, vol. 8, pp. 229219–229233, Dec. 2020, doi: 10.1109/ACCESS.2020.3047077.

[25]. Y. Shrestha, Y. Zhang, G. M. McFarquhar, W. Blake, M. Starzec, and S. D. Harrah, "Development of Simulation Models Supporting Next-Generation Airborne Weather Radar for High Ice Water Content Monitoring," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 16, pp. 493–508, 2023, doi: 10.1109/JSTARS.2022.3227124.

[26]. A. Bojesomo, H. AlMarzouqi, and P. Liatsis, "A Novel Transformer Network With Shifted Window Cross-Attention for Spatiotemporal Weather Forecasting," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 17, pp. 45–56, 2024.

[27]. J. Kim and S. Kim, "A Study on Estimating Theme Park Attendance Using the AdaBoost Algorithm Based on Weather Information," J. Web Eng., vol. 23, no. 6, pp. 869–884, 2024.

[28]. N. Wedi et al., "Destination Earth: High-Performance Computing for Weather and Climate," Comput. Sci. Eng., vol. 24, no. 6, pp. 29–37, Nov.–Dec. 2022.

[29]. Jinkook Kim and Soohyun Kim, "A Study on Estimating Theme Park Attendance Using the AdaBoost Algorithm Based on Weather Information from the Korea Meteorological Administration Web," Journal of Web Engineering, Vol. 23_6, 869-884, 2024.

[30]. Z. Tang, J. Liu, J. Ni, J. Zhang, P. Zeng, P. Ren, and T. Su, "Power Prediction of Wind Farm Considering the Wake Effect and its Boundary Layer Compensation," IEEE Access, vol. 8, pp. 1234-1244, 2024.

[31]. J. Montaña, C. Valle, S. Rosales, R. Schurch, and D. Pozo, "Predicting Algorithm of Thunderstorm Days in the Northern Region of Chile Using Convolution Neural Network," IEEE Access, vol. 12, pp. 3445320, 2024.

[32]. Y. Zhou, Y. Sun, S. Wang, R. J. Mahfoud, D. Hou, and J. Wang, "Very Short-term Probabilistic Prediction for Regional Wind Power Generation Based on OPNPIS," CSEE Journal of Power and Energy Systems, doi: 10.17775/CSEEJPES.2022.02790.

[33]. J. Lee, J. Kang, S. Son, and H. -M. Oh, "Numerical Weather Data-Driven Sensor Data Generation for PV Digital Twins: A Hybrid Model Approach," IEEE Access, vol. 13, pp. 3525659, 2025.

[34]. J. Faraji, A. Ketabi, H. Hashemi-Dezaki, M. Shafie-Khah, and J. P. S. Catalão, "Optimal Day-Ahead Self-Scheduling and Operation of Prosumer Microgrids Using Hybrid Machine Learning-Based Weather and Load Forecasting," IEEE Access, vol. 8, pp. 3019562, 2020.

[35]. N. Uthayansuthi and P. Vateekul, "Optimization of Peer-to-Peer Energy Trading With a Model-Based Deep Reinforcement Learning in a Non-Sharing Information Scenario," IEEE Access, vol. 12, pp. 3442445, 2024.

[36]. S. Choi and E. -S. Jung, "Optimizing Numerical Weather Prediction Model Performance Using Machine Learning Techniques," IEEE Access, vol. 11, pp. 3297200, 2023.

[37]. C. Zoremsanga and J. Hussain, "Particle Swarm Optimized Deep Learning Models for Rainfall Prediction: A Case Study in Aizawl, Mizoram," IEEE Access, vol. 12, pp. 3390781, 2024.

[38]. C. Senogz, S. Ramanna, S. Kehler, R. Goomer, and P. Pries, "Machine Learning Approaches to Improve North American Precipitation Forecasts," IEEE Access, vol. 11, pp. 3309054, 2023.

[39]. M. M. Hassan, M. A. T. Rony, M. A. R. Khan, M. M. Hassan, F. Yasmin, A. Nag, T. H. Zarin, A. K. Bairagi, S. Alshathri, and W. El-Shafai, "Machine Learning-Based Rainfall Prediction: Unveiling Insights and Forecasting for Improved Preparedness," IEEE Access, vol. 11, pp. 3333876, 2023.

[40]. M. Zhao and X. Zhou, "Multi-Step Short-Term Wind Power Prediction Model Based on CEEMD and Improved Snake Optimization Algorithm," IEEE Access, vol. 12, pp. 3385643, 2024.

[41]. S. Surendran, M. V. Ramesh, A. Montresor, and M. J. Montag, "Link Characterization and Edge-Centric Predictive Modeling in an Ocean Network," IEEE Access, vol. 11, pp. 3235387, 2023.

[42]. M. M. Hassan, M. A. T. Rony, M. A. R. Khan, M. M. Hassan, F. Yasmin, A. Nag, T. H. Zarin, A. K. Bairagi, S. Alshathri, and W. El-Shafai, "Machine Learning-Based Rainfall Prediction: Unveiling Insights and Forecasting for Improved Preparedness," IEEE Access, vol. 11, pp. 3333876, 2023.

[43]. CHENG LYU, (Graduate Student Member, IEEE), AND SARA EFTEKHARNEJAD, (Senior Member, IEEE), "Probabilistic Solar Generation Forecasting for Rapidly Changing Weather Conditions," IEEE Access, vol., pp., 2024.

[44]. CHRISTIAN GIANOGLIO 1, (Member, IEEE), SARA ZANI 2, MATTEO COLLI 2, AND DANIELE D. CAVIGLIA 1, (Life Member, IEEE), "Rainfall Classification in Genoa: Machine Learning Versus Adaptive Statistical Models Using Satellite Microwave Links," IEEE Access, vol. 12, pp. 132743 - 132752, 2024.

[45]. NANA KOFI AHOI APPIAH-BADU1.2, YAW MARFO MISSAH[1], LEONARD K. AMEKUDZI[3], NAJIM USSIPH[1], TWUM FRIMPONG[1], AND EMMANUEL AHENE1, "Rainfall Prediction Using Machine Learning Algorithms for the Various Ecological Zones of Ghana," IEEE Access, vol. 10, pp. 5082 - 5095, 2022.

[46]. Yihe Zhang, Bryce Turney, Purushottam Sigdel, Xu Yuan, Eric Rappin, Adrian L. Lago, Sytske Kimball, Li Chen, Paul Darby, Lu Peng, Sercan Aygun, Yazhou Tu, M. Hassan Najafi, and Nian-Feng Tzeng, "Regional Weather Variable Predictions by Machine Learning With Near-Surface Observational and Atmospheric Numerical Data," IEEE Transactions on Geoscience and Remote Sensing, vol. 63, 2025, pp. 1-16.

[47]. M. M. Asiri, G. Aldehim, F. A. Alotaibi, M. M. Alnfiai, M. Assiri, and A. Mahmud, “Short-Term Load Forecasting in Smart Grids Using Hybrid Deep Learning,” IEEE Access, vol. 12,

pp. 23504–23512, Jan. 2024, doi: 10.1109/ACCESS.2024.3358182.

[48]. H. Kim, S. Park, H.-J. Park, H.-G. Son, and S. Kim, “Solar Radiation Forecasting Based on the Hybrid CNN-CatBoost Model,” IEEE Access, vol. 11, pp. 13492–13498, Feb. 2023, doi: 10.1109/ACCESS.2023.3243252.

[49]. S. Wang, Y. Li, B. Yang, and R. Duan, "Short-Term Forecasting of Convective Weather Affecting Civil Aviation Operations Using Deep Learning," IEEE Access, vol. 12, pp. 116603-116614, 2024.

[50]. S. Tsegaye, S. Padmanaban, L. B. Tjernberg, and K. A. Fante, "Short-Term Load Forecasting for Electrical Power Distribution Systems Using Enhanced Deep Neural Networks," IEEE Access, vol. 12, pp. 186871-186884, 2024.

[51]. M. Yang, K. Wang, X. Su, M. Ma, G. Wu, and D. Huang, "Short-Term Photovoltaic Output Probability Prediction Method Considering the Spatio-Temporal-Conditional Dependence of Prediction Error," DOI: 10.17775/CSEEJPES.2022.02360.

[52]. T. Lin and R. Lin, "Smart City Traffic Flow and Signal Optimization Using STGCN-LSTM and PPO Algorithms," IEEE Access, vol. 13, pp. 15078-15091, 2025.

[53]. A. Guo, Y. Liu, S. Shao, X. Shi, and Z. Feng, "Spatial-Temporal Fusion Graph Neural Networks With Mixed Adjacency for Weather Forecasting," IEEE Access, vol. 13, pp. 15824-15833, 2025.

[54]. X. Zhang et al., "StHCFormer: A Multivariate Ocean Weather Predicting Method Based on Spatiotemporal Hybrid Convolutional Attention Networks," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 3610-3626, 2024.

[55]. Ş. Özdemir, Y. Demir, and Ö. Yıldırım, "The Effect of Input Length on Prediction Accuracy in Short-Term Multi-Step Electricity Load Forecasting: A CNN-LSTM Approach," IEEE Access, vol. 13, pp. 28432-28443, 2025.

[56]. T. A. Gahwera, O. S. Eyobu, M. Isaac, S. Kakuba, and D. S. Han, "Transfer Learning-Based Ensemble Approach for Rainfall Class Amount Prediction," IEEE Access, vol. 13, pp. 48334-48344, 2025.

[57]. S. Wang and O. Xu, "Uncertainty Forecasting Model for Mountain Flood Based on Bayesian Deep Learning," IEEE Access, vol. 12, pp. 3384066-3384077, 2024.

[58]. M. K. Saravana, M. S. Roopa, J. S. Arunalatha, and K. R. Venugopal, “Temporal Harmony: Bridging Gaps in Multivariate Time Series Data with GAN-Transformer Integration,” in Proc of the 2024 IEEE Int. Conf. Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), vol. 2, pp. 1–6, 2024. IEEE

[59]. M. K. Saravana, M. S. Roopa, J. S. Arunalatha, and K. R. Venugopal, “Navigating Data Scarcity in Multivariate Time Series Forecasting: A Hybrid Model Perspective,” in Proceedings of the 2024 IEEE Region 10 Symposium (TENSYMP), pp. 1–7, 2024. IEEE

[60]. M. K. Saravana, M. S. Roopa, J. S. Arunalatha, and K. R. Venugopal, “Graph Laplacian Eigenvalues Empowered VAEs: A Novel Approach to Adaptive Latent Dimension Choice,” IEEE Access, vol. 12, pp. 135265–135282, 2024, doi: 10.1109/ACCESS.2024.3460971.

[61]. M. K. Saravana, M. S. Roopa, J. S. Arunalatha, and K. R. Venugopal, “Unsupervised MTS Anomaly Detection with Variational Autoencoders,” in Lecture Notes in Networks and Systems, in Proceedings of the 4th Int. Conf. Front. Comput. Syst., Singapore, 2024, vol. 974, pp. 219–236, Springer Nature Singapore.