

Unveiling Time Series Forecasting: A Deep Dive into Machine Learning Approaches

Pradnya P. Shelar¹ and Monika Bhatnagar²

^{1,2}Department of Computer Science & Engineering, Oriental University, Indore, MP, India
Email: pradnyak.bachhav@gmail.com, monikabhatnagar@oriental.ac.in

Abstract— Time series forecasting has become essential in various industries, including finance, energy, healthcare, and environmental science, where accurate predictions drive strategic decision-making. This work examines deep learning-based time-series forecasting models for non-stationary and non-linear data, focusing on LSTM based hybridized model that enhance long-term dependencies and predictive accuracy. This also explores decomposition-based hybrid models that uses trend-seasonality and wavelet methods, along with advanced models like Temporal Fusion Transformers (TFT) and LSTM-CNN combinations. Despite their success, these models face challenges like computational complexity, overfitting, and limited adaptability to extreme events. Key research gaps include real-time data integration, interpretability, and computational efficiency. Future research directions should enhance model robustness, incorporate external variables, and develop lightweight architectures for real-time forecasting. Closing these gaps will facilitate more efficient forecasting models, enhancing decisions in critical domains like energy, finance, and healthcare.

Index Terms— Time Series Forecasting, Deep Learning, Hybrid Models, LSTM, Transformer, TFT.

I. INTRODUCTION

A. Overview of the Domain

The analytical process of time series forecasting relies on historical data to predict future values by identifying temporal patterns, making it essential for domains requiring past trends to impact future results, such as economics, healthcare, supply chains, and climate science [1] – [3].

Time series forecasting is essential for industries to improve operations, minimize uncertainty and enhance strategic planning [2] – [5]. In financial analysis, it supports stock price prediction, volatility assessment, and algorithmic trading, with the market projected to expand from \$11.1 billion in 2020 to \$18.8 billion by 2025 (by Bain & Co). Accurate forecasting in energy helps in optimizing grid operations and reducing costs. In healthcare, it aids in epidemic prediction, patient tracking, and resource allocation—minimizing disease outbreak response time by 30% as shown by CDC studies.

Forecasting also supports climate disaster readiness and enables supply chain management of organizations. Such techniques can reduce inventory costs by 10–20% and improve service levels by 20–30% according to research by McKinsey & Company [6]. The quick growth of digital data collection combined with ML and DL methods have redefined time series forecasting.

Traditional forecasting methods like ARIMA [7]-[9] and exponential smoothing are used, yet they struggle with capturing nonlinear patterns and long-term dependencies. In contrast, machine learning models showed excellence in handling complex, multivariate, and non-stationary data [10].

Despite growing interest, research in time series forecasting remains fragmented, often focused on specific models or niche applications. Key issues—like handling missing data, extreme events, and model interpretability—are often addressed in isolation, leading to a lack of comprehensive evaluation frameworks.

This research aims to bridge the gap by systematically assessing forecasting techniques, highlighting their trade-offs, and identifying areas needing further investigation.

B. Problem Statement and Objective

Problem Statement

Despite the growing advancements in time series forecasting, there is a lack of comprehensive research comparing different models in terms of accuracy, efficiency, and adaptability across various applications. Most studies focus on individual models or specific techniques without a holistic evaluation of their relative performance. This gap makes it difficult to determine the most effective forecasting approach for different scenarios. This research aims to address this limitation by systematically analysing and comparing various time series forecasting models to identify their methodology, strengths, and weaknesses, and suggest future directions for research in this sub-domain.

Objective

- To systematically compare the methodologies of various time series forecasting models, evaluating their computational frameworks and predictive approaches.
- To identify the key advantages of these models, focusing on their accuracy, efficiency, and ability to handle complex temporal patterns.
- To analyse the limitations and challenges associated with these models, focusing on factors such as accuracy, generalizability, scalability, and practical applicability.
- To identify key research gaps in the reviewed work, and suggest future directions for improving forecasting models with a focus on efficiency, scalability, and accuracy.

C. Structure of the Research

After this introduction section, the very next section explores the integration of LSTM with various feature engineering techniques like PCA, tree-based models and auto-encoders. The section ahead focuses on decomposition techniques that enhance forecasting accuracy by separating time series components, also known as decomposition-based models. Further, even more advanced Hybrid Models for Time Series Forecasting are explored. Further, the discussion section synthesizes insights from the reviewed studies, focusing on key findings, model strengths, limitations, research gaps, and real-world applications. Finally, the conclusion section provides a summary of key insights, emphasizing the role of hybrid models in improving time series forecasting accuracy and efficiency, and suggests future directions.

II. FEATURE ENGINEERING-BASED HYBRID MODELS

This section focuses on research that integrates feature engineering techniques with hybrid deep learning models to enhance time-series forecasting accuracy.

A. LSTM with PCA architecture

Time-series forecasting has gained significant attention across various domains, from energy consumption to financial markets. In [11], researchers explored innovative ways to improve the accuracy of residential electricity consumption forecasting. The study aimed to enhance predictive performance by leveraging feature engineering and Long Short-Term Memory (LSTM) networks. The study integrated lag/window features with PCA to improve LSTM accuracy but did not include hyperparameter tuning for further optimization.

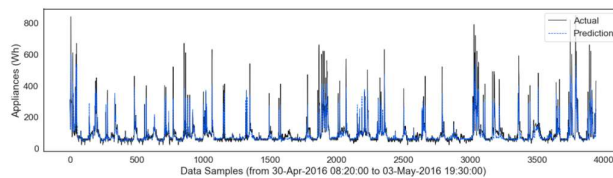


Fig 1: Actual vs Predicted values in [11]

Figure 1 presents a comparison between the predicted and actual values for the first 500 test data points. The solid line represents the actual recorded values, whereas the dotted line illustrates the model's forecasted results. Beyond time-series forecasting, deep learning techniques have also been applied in medical research, as seen in [12], where an RNN-based model classified Alzheimer's disease using EEG data.

The methodology involved Principal Component Analysis (PCA) for feature extraction and Robust PCA (RPCA) for filtering outlier noise before RNN-based classification (Fig. 2.2). The key contribution of the study was RPCA's robustness but it lacked explorations of other architectures like CNNs or Transformers, and focused solely on AD classification. A key limitation in [11-12] includes feature alignment between LSTM-generated representations and PCA.

B. LSTM with Tree based Models

The financial forecasting in [13] used LSTM and Random Forest for S&P 500 (1993–2018) price prediction, demonstrating improved returns and risk-adjusted performance over single-feature models, although the computational costs remained high.

Recently a three-model hybrid was exploited for time series prediction. [14] proposed a CNN-LSTM-XGBoost hybrid model for stock price forecasting, leveraging attention mechanisms and sequence-to-sequence learning, which outperformed standalone models. However, the study solely relied on historical data without considering macroeconomic indicators or alternative feature selection techniques.

Figure 2 represents the implementation architecture of CNN-LSTM-XGBoost hybrid model for stock price forecasting in [14].

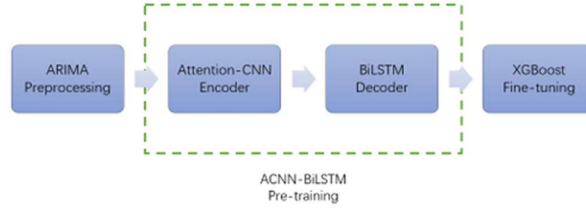


Fig 2. Implementation Architecture in [14]

C. LSTM with Autoencoder-Based Feature Extraction

LSTM-Autoencoder hybrids are effective for time-series anomaly detection essential for identifying hazardous deviations. In [15], a model was proposed for indoor air quality monitoring, combining LSTM for temporal pattern learning and Autoencoder for reconstruction-based anomaly detection. Trained on the Dunedin CO₂ dataset, it achieved 99.5% accuracy.

Beyond anomaly detection, [16] applied an LSTM-Autoencoder model for power load forecasting using a dual-channel encoder-decoder to capture both long- and short-term dependencies architecture, as shown in Fig. 3.

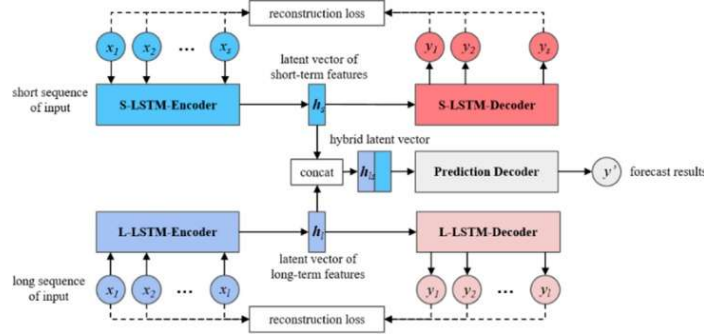


Fig.3: Architecture followed in [16]

Trained on the Alberta Electric System dataset, the LSTM-Autoencoder model achieved an MAE of 51.83 MW, outperforming LSTM and GRU baselines. While its multi-level feature extraction improved generalization, the model struggled with load peaks and troughs, suggesting a need for dynamic adaptation mechanisms.

Table I summarizes the research reviewed in this section.

TABLE I: SUMMARY OF RESEARCHES STUDIED

Study	Methodology	Advantages	Limitations	Research Gap
[11]–[12]	PCA-LSTM, PCA+RPCA+RNN for electricity, stock, and AD detection	Improved accuracy, reduced features, robust to missing data	Tracking errors, limited dynamic trend capture, no CNN/Transformer integration	Feature alignment and dynamic trend modelling in PCA-hybrids
[13]	RF-LSTM hybrids for stock prediction	Better feature selection, higher returns	High cost, limited generalization	Feature ranking stability over time
[14]	CNN-LSTM-XGBoost for stock forecasting	High accuracy, good trend capture	No macroeconomic factors	Needs adaptive feature integration
[15]–[16]	LSTM-Autoencoder for anomaly & power load detection	High accuracy, good generalization	Sensitive to reconstruction loss, poor at extremes	Adaptive thresholding and peak handling

III. DECOMPOSITION-BASED HYBRID MODELS FOR TIME-SERIES FORECASTING

This method involves models that decompose time series into multiple components, applying different forecasting methods to each.

A. Trend-Seasonality Decomposition

Time series forecasting often requires handling both trend and seasonal variations. One such study [17] introduced an STL-GRU model that combined seasonal-trend decomposition with GRU for temperature prediction. Evaluated on three datasets from Gansu Province, China, the model achieved lower RMSE values than baseline models, as validated by the Diebold–Mariano test.

A visual representation of the STL-GRU model architecture is depicted in Figure 4.

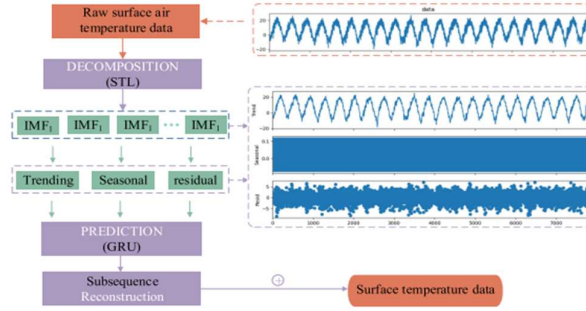


Fig 4: STL-GRU Architecture in [17]

While the decomposition improved performance, its sensitivity to seasonal instability and GRU's reliance on long data histories limit adaptability.

In [18], a hybrid short-term load forecasting model used MIC and boosting-based feature selection (LightGBM, XGBoost), followed by an error correction mechanism. The model outperformed baselines with up to 2.68% MAPE reduction. However, reliance on boosting models limits adaptability in volatile environments compared to deep learning alternatives.

CNN captures seasonal variations, LSTM models long-term dependencies, and GPR handles residual noise, enhancing prediction accuracy

B. Wavelet-based Decomposition

A study on hybrid EMD-Wavelet LSTM [19] was introduced for groundwater level forecasting to address non-stationarity. By integrating Empirical Mode Decomposition (EMD) and Wavelet Transform (WT), the model effectively captured underlying trends surpassing traditional LSTM and Wavelet-LSTM models. However, it struggled with highly stochastic variations, limiting its effectiveness in unpredictable settings.

Similarly, in [20], W-DSTAGNN, a wavelet-enhanced graph neural network, improved traffic flow forecasting by extracting multi-resolution temporal patterns. It outperformed other models, but its effectiveness heavily relied on optimal wavelet parameter tuning, making its adaptability challenging.

In another study [21], wavelet-based denoising was applied to electricity demand forecasting, improving ARIMA's performance over standalone models. The approach notably enhanced forecasting precision, confirming the utility of wavelet preprocessing.

Table II. summarizes the literature reviewed in this section.

TABLE II: SUMMARY OF THE LITERATURE REVIEWED

Study	Methodology	Advantage	Limitation	Research Gap
[17]–[18]	STL-based hybrid models (GRU, LSTM, CNN, GPR)	Capture trends and seasonality; improve RMSE, MAPE	Depend on decomposition accuracy; high complexity	Adaptive GRU/LSTM for short data; reduce model complexity
[19]	EMD-Wavelet-LSTM for groundwater prediction	Handles non-stationarity; large RMSE reduction	Ineffective for stochastic variations	Improve handling of random fluctuations
[20]	W-DSTAGNN for traffic flow forecasting	Strong spatiotemporal learning; top performance	Sensitive to noise; tuning dependent	Robust tuning methods; noise-resilient design
[21]	Coiflet Wavelet + ARIMA & ES for electricity forecasting	Wavelet preprocessing boosts accuracy significantly	Sensitive to wavelet type; computational load	Broader wavelet testing; improve scalability

IV. ADVANCED HYBRID MODELS FOR TIME SERIES FORECASTING

This sub-section explores various other advanced hybrid models, which utilize transformers and deep learning for time series forecasting.

A. Temporal Fusion Transformer (TFT)

Recent advancements have popularized transformer-based architectures for time series forecasting. In [22], a Temporal Fusion Transformer (TFT) outperformed LSTM, Interpretable LSTM, and TCN in daily to monthly energy forecasting, achieving the lowest MSE (4.09), RMSE (2.02), and MAE (1.50), though its robustness under extreme fluctuations was not evaluated.

In [23], TFT showed elevated performance at the substation level (2.43% MAPE) and for week-ahead forecasts (2.52% MAPE), though it trailed LSTM at the grid level. The study noted TFT's multi-level forecasting potential but lacked interpretability analysis.

B. CNN Hybridized with LSTM Models

Deep learning has gained attention in financial forecasting due to its ability to capture nonlinear stock patterns. In [24], CNN and LSTM models predicted stock prices using high-frequency NSE data, demonstrating promising RMSE performance.

In a broader financial context, [25] developed a CNN-LSTM hybrid model for forecasting multiple Asian stock indices, excelling during COVID-19-induced volatility. While effective, the model lacked real-time adaptability due to retraining requirements. The CNN-LSTM model implemented in [25] is shown in Fig 5.

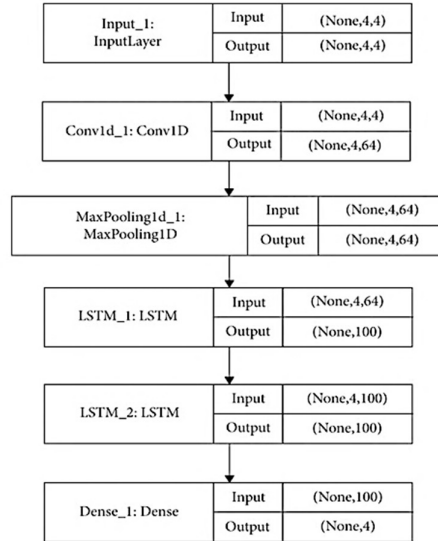


Fig 5: Implemented model in [25]

Similarly, [26] used a CNN-LSTM model for PV Power Generation forecasting in Busan, Korea, performing better on sunny days but showing sensitivity to abrupt weather changes and increased complexity from redundant features.

For short-term load forecasting, [27] applied a CNN-LSTM model on Pakistan's NTDC dataset, achieving low RMSE and MAPE for single-step prediction. However, its performance degraded in 24-hour forecasts, highlighting challenges in handling long-term dependencies and load volatility.

The summary of studies reviewed in this section is presented in table III

TABLE III: SUMMARY OF STUDIES REVIEWED IN IV

Study	Methodology	Advantages	Limitations	Research Gap
[22]	TFT for short-term energy/load forecasting	Outperforms ARIMA, LSTM; low RMSE & MAE	Not tested under seasonal or extreme demand shifts	Needs evaluation under volatility and seasonal effects
[23]	TFT for day/week-ahead electricity load	Strong week-ahead and substation-level results	No interpretability analysis	Feature contribution analysis missing
[24]-[25]	CNN-LSTM for stock/financial forecasting	Captures trends well; best RMSE among peers	Slow to adapt, long training time	Real-time adaptability; hybrid comparisons
[26]	CNN-LSTM-TF for solar forecasting	Accurate spatial-temporal learning;	Fixed training window; redundant features	Needs dynamic adaptation and feature optimization
[27]	CNN-LSTM for short-term load forecasting	Superior single-step prediction accuracy	Weaker long-term forecasting	Improve handling of long-term dependencies

V. DISCUSSION

A. Key Findings and Trends

Recent advancements in time series forecasting favour hybrid deep learning models such as CNN, LSTM, Transformers, and wavelet-based architectures. The Temporal Fusion Transformer (TFT) consistently outperforms LSTM and TCN in energy and solar forecasting, while CNN-LSTM models excel in financial prediction by capturing spatial-temporal features.

Additionally, decomposition techniques like Wavelet Transform, EMD, and STL improve model accuracy by denoising and extracting periodic trends. Hybrid models combining these techniques with LSTM, CNN, and GPR have shown significant improvements in electricity and groundwater forecasting, emphasizing the value of pre-processing [28].

Spatiotemporal models, including W-DSTAGNN and wavelet-based burst prediction, outperform traditional methods in traffic and fluid flow prediction. However, their sensitivity to parameter tuning and noise, limits real-world adaptability.

B. Strengths and Advantages of ML Models for Time Series Prediction

- Improved Forecasting Accuracy: Hybrid models consistently outperformed standalone models like ARIMA and LSTM, as seen in financial forecasting, energy forecasting, and load forecasting.
- Handling Long-Term Dependencies: TFT demonstrated superior long-range dependencies, especially in energy demand forecasting [29]-[31]. On the contrary, CNN-LSTM models captured better trend forecasting in financial and renewable energy domains.
- Noise Reduction and Feature Extraction: Wavelet-based models significantly improved forecasting performance by filtering out noise in time series data prediction.
- Multi-Level Performance Optimization: TFT performed better at substation levels, while CNN-LSTM demonstrated adaptability across different forecasting horizon.

C. Limitations of ML Models for Time Series Prediction

- Data Dependency and Quality Issues: ML models require large, high-quality datasets, but real-world time series data often contain missing values, noise, and non-stationarity, making pre-processing essential for reliable forecasting [33].
- Computational Complexity: Deep learning models require significant computational resources, limiting real-time applicability. [34]
- Overfitting and Generalization Challenges: ML models may struggle to generalize, particularly with limited or highly variable datasets.

D. Real World Applications of the work

- Financial Market Prediction: The models analysed in this research will help improve stock price forecasting, risk assessment, and algorithmic trading [32].
- Energy Demand and Load Forecasting: The suggested models will enhance grid stability, reduce costs, and improve the integration of renewable energy sources like solar and wind power by providing more precise demand predictions.
- Healthcare and Disease Progression Modelling: By leveraging the forecasting approaches discussed in this research, healthcare systems can better predict disease outbreaks, patient health trends, and resource allocation needs.
- Supply Chain and Demand Forecasting: The insights from this research can be used to improve demand forecasting, optimize inventory management, and enhance logistics planning, thereby improving cost efficiency and inventory control.

E. Future Directions

Time series forecasting through machine learning has advanced considerably, yet multiple research gaps remain in hybrid model development. Integration of CNN-LSTM offers effective predictive performance by combining feature extraction and temporal learning, but existing literature on this architecture is limited.

The integration of LSTMs with tree-based methods like random forests enhances decision-making and interpretability, showing promise for time series applications, though optimization processes remain underexplored.

Hybrid models combining LSTMs with graph neural networks (GNNs) remain largely unexplored, despite their potential to model complex interdependencies in multi-variable time series data, such as in finance, transport, and climate systems. GNNs enhance forecasting accuracy by capturing relational elements that complement LSTM's temporal learning.

VI. CONCLUSION

Time series forecasting represents an essential tool that works across financial sectors and energy systems as well as healthcare institutions and supply chain operations. Studies about these models exist as individual research, which hinder the ability to perform comprehensive methodological study and limitation assessment.

The study delivers an extensive exploration of different time series forecasting techniques by presenting their methodology, along with their main advantages and limitations. This research implements systematic model comparison to deliver important findings regarding their practical use and performance capabilities.

Researchers should direct future investigations toward hybrid models, especially for CNN-LSTM and combinations of LSTM with tree-based models and LSTM with graph neural networks since these methods successfully enhance prediction accuracy together with robustness. Advancing the field requires both improvement of computational abilities and enhanced model generalization capabilities.

The research outcomes will provide direction to practitioners along with researchers who need to select and enhance forecasting models for actual implementation scenarios. This investigation connects missing knowledge in previous research to advance the creation of more dependable and effective and understandable forecasting approaches.

REFERENCES

- [1] Ghazal, Taher M. "Energy demand forecasting using fused machine learning approaches." *Intelligent Automation & Soft Computing* 31.1 (2022): 539-553.
- [2] Ferreira, Andréia BA, Jonatas B. Leite, and Denis HP Salvadeo. "Power substation load forecasting using interpretable transformer-based temporal fusion neural networks." *Electric Power Systems Research* 238 (2025): 111169.
- [3] Zheng, Haotian, et al. "Predicting financial enterprise stocks and economic data trends using machine learning time series analysis." *Applied and Computational Engineering* 87 (2024): 26-32.
- [4] Tang, Qi, et al. "Prediction of financial time series based on LSTM using wavelet transform and singular spectrum analysis." *Mathematical Problems in Engineering* 2021.1 (2021): 9942410.
- [5] Lawi, Armin, Hendra Mesra, and Supri Amir. "Implementation of Long Short-Term Memory and Gated Recurrent Units on grouped time-series data to predict stock prices accurately." *Journal of Big Data* 9.1 (2022): 89.
- [6] Wunsch, Andreas, Tanja Liesch, and Stefan Broda. "Groundwater level forecasting with artificial neural networks: a comparison of long short-term memory (LSTM), convolutional neural networks (CNNs), and non-linear autoregressive networks with exogenous input (NARX)." *Hydrology and Earth System Sciences* 25.3 (2021): 1671-1687..

- [7] Jakhmola, Yash, et al. "Wavelet-based Temporal Attention Improves Traffic Forecasting." arXiv e-prints (2024): arXiv-2407.
- [8] Guermoui, Mawloud, et al. "An analysis of case studies for advancing photovoltaic power forecasting through multi-scale fusion techniques." *Scientific Reports* 14.1 (2024): 6653.
- [9] Dikshit, Abhirup, Biswajeet Pradhan, and Abdullah M. Alamri. "Long lead time drought forecasting using lagged climate variables and a stacked long short-term memory model." *Science of The Total Environment* 755 (2021): 142638.
- [10] Kirisci, Melih, and Ozge Cagcag Yolcu. "A new CNN-based model for financial time series: TAIEX and FTSE stocks forecasting." *Neural Processing Letters* 54.4 (2022): 3357-3374.
- [11] Suranata, I. Wayan Aditya, et al. "Feature engineering and long short-term memory for energy use of appliances prediction." *TELKOMNIKA (Telecommunication Computing Electronics and Control)* 19.3 (2021): 920-930.
- [12] Alessandrini, Michele, et al. "Eeg-based alzheimer's disease recognition using robust-pca and lstm recurrent neural network." *Sensors* 22.10 (2022): 3696.
- [13] Ghosh, Pushpendu, Ariel Neufeld, and Jajati Keshari Sahoo. "Forecasting directional movements of stock prices for intraday trading using LSTM and random forests." *Finance Research Letters* 46 (2022): 102280.
- [14] Shi, Zhuangwei, et al. "Attention-based CNN-LSTM and XGBoost hybrid model for stock prediction." arXiv preprint arXiv:2204.02623 (2022).
- [15] Wei, Yuanyuan, et al. "LSTM-autoencoder-based anomaly detection for indoor air quality time-series data." *IEEE Sensors Journal* 23.4 (2023): 3787-3800.
- [16] Tong, Xin, et al. "LS-LSTM-AE: Power load forecasting via Long-Short series features and LSTM-Autoencoder." *Energy Reports* 8 (2022): 596-603.
- [17] Liu, Xiao, and Qianqian Zhang. "Combining Seasonal and Trend Decomposition Using LOESS with a Gated Recurrent Unit for Climate Time Series Forecasting." *IEEE Access* (2024).
- [18] Yao, Xiaotong, Xiaoli Fu, and Chaofei Zong. "Short-term load forecasting method based on feature preference strategy and LightGBM-XGboost." *IEEE Access* 10 (2022): 75257-75268.
- [19] Nazari, Amirhossein, et al. "Groundwater level forecasting using empirical mode decomposition and wavelet-based long short-term memory (LSTM) neural networks." *Groundwater for Sustainable Development* 28 (2025): 101397.
- [20] Jakhmola, Yash, et al. "Spatiotemporal Forecasting of Traffic Flow using Wavelet-based Temporal Attention." *IEEE Access* (2024).
- [21] Kumar, Mohit, and Jatinder Kumar. "Impact of Coiflet Wavelet Decomposition on Forecasting Accuracy: Shifts in ARIMA and Exponential Smoothing Performance." *Metallurgical and Materials Engineering* 31.1 (2025): 177-192.
- [22] Nazir, Amril, et al. "Forecasting energy consumption demand of customers in smart grid using Temporal Fusion Transformer (TFT)." *Results in Engineering* 17 (2023): 100888.
- [23] Giacomazzi, Elena, Felix Haag, and Konstantin Hopf. "Short-term electricity load forecasting using the temporal fusion transformer: Effect of grid hierarchies and data sources." *Proceedings of the 14th ACM international conference on future energy systems*. 2023.
- [24] Mehtab, Sidra, and Jaydip Sen. "Analysis and forecasting of financial time series using CNN and LSTM-based deep learning models." *Advances in Distributed Computing and Machine Learning: Proceedings of ICADCML 2021*. Springer Singapore, 2022.
- [25] Widiputra, Harya, Adele Mailangkay, and Elliana Gautama. "Multivariate CNN-LSTM model for multiple parallel financial time-series prediction." *Complexity* 2021.1 (2021): 9903518.
- [26] Lim, Su-Chang, et al. "Solar power forecasting using CNN-LSTM hybrid model." *Energies* 15.21 (2022): 8233.
- [27] Ullah, Kaleem, et al. "Short-term load forecasting: A comprehensive review and simulation study with CNN-LSTM hybrids approach." *IEEE Access* (2024).
- [28] Soori, Mohsen, Behrooz Arezoo, and Roza Dastres. "Machine learning and artificial intelligence in CNC machine tools, a review." *Sustainable Manufacturing and Service Economics* 2 (2023): 100009.
- [29] Forootan, Mohammad Mahdi, et al. "Machine learning and deep learning in energy systems: A review." *Sustainability* 14.8 (2022): 4832.
- [30] Shapi, Mel Keytingan M., Nor Azuana Ramli, and Lilik J. Awal. "Energy consumption prediction by using machine learning for smart building: Case study in Malaysia." *Developments in the Built Environment* 5 (2021): 100037.
- [31] Rouf, Nusrat, et al. "Stock market prediction using machine learning techniques: a decade survey on methodologies, recent developments, and future directions." *Electronics* 10.21 (2021): 2717.
- [32] Wu, Dingming, Xiaolong Wang, and Shaocong Wu. "Jointly modeling transfer learning of industrial chain information and deep learning for stock prediction." *Expert Systems with Applications* 191 (2022): 116257.
- [33] Ghannam, Ryan B., and Stephen M. Techtman. "Machine learning applications in microbial ecology, human microbiome studies, and environmental monitoring." *Computational and Structural Biotechnology Journal* 19 (2021): 1092-1107.
- [34] Zhu, Mengyuan, et al. "A review of the application of machine learning in water quality evaluation." *Eco-Environment & Health* 1.2 (2022): 107-116.