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Research Article

The Evolution of Time Series Analysis: Beyond Traditional Forecasting

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Abstract:

The field of time series forecasting has undergone a profound transformation, evolving from traditional statistical foundations to sophisticated deep learning innovations. Modern neural networks and machine learning models now offer enhanced capabilities for capturing complex patterns and non-linear relationships, often surpassing conventional approaches. Key architectural advancements, such as attention mechanisms and transformer architectures, have revolutionized the processing of sequential data. Concurrently, the emergence of automated machine learning (AutoML) and explainable AI (XAI) has significantly streamlined model development and improved interpretability. These developments hold particular significance for domains requiring multi-dimensional analysis and real-time predictions, where advanced architectures excel at discerning intricate relationships between variables while maintaining computational efficiency.

1. Introduction

Time series forecasting has undergone a remarkable transformation over the past decade, with the landscape shifting dramatically from traditional statistical approaches to sophisticated machine learning methodologies. Neural networks and machine learning models have demonstrated enhanced capabilities in handling complex patterns and non-linear relationships compared to conventional methods. A comprehensive empirical study by Ahmed and Atiya analyzed ten machine learning models, identifying multilayer perceptrons (a type of neural network) and Gaussian process regression as top performers among the machine learning methods [1]. The study revealed that machine learning approaches generally excel at capturing complex, non-linear dynamics and extracting intricate features from data, particularly when dealing with irregular patterns and multiple seasonal cycles.

While the overall performance of neural networks in large-scale competitions has shown mixed results against traditional statistical methods, with simpler methods sometimes outperforming individual deep learning models, the landscape has evolved significantly. Machine learning approaches have demonstrated particular strength in scenarios involving high-dimensional data and complex temporal dependencies. Recent developments in evolutionary neural architecture search have shown promising results in automatically discovering optimal network structures for multivariate non-stationary time series forecasting, addressing one of the key challenges in applying deep learning to temporal data [2].

The integration of machine learning in time series analysis has transformed not just the accuracy metrics but the entire approach to temporal data processing. Traditional statistical methods, while effective for linear and well-structured data, often struggle with complex patterns and multiple seasonal cycles. The empirical analysis has shown that machine learning models offer advantages in handling missing values and outliers more effectively, often with improved processing efficiency compared to traditional methods [1]. This improvement in processing efficiency, combined with enhanced pattern recognition capabilities, has made machine learning approaches increasingly attractive for real-world applications.

The advancement in forecasting capabilities has particularly benefited sectors dealing with complex, non-linear patterns. Modern deep learning architectures have demonstrated superior performance in capturing intricate relationships between variables, with evolutionary approaches showing impressive ability to adapt to changing patterns in non-stationary environments [2]. This enhancement in adaptive capability has proven especially valuable in critical applications such as energy demand forecasting, financial market prediction, and resource optimization, where traditional methods often fall short.

2. Historical Foundation and Evolution

The evolution of time series analysis represents a fascinating journey through statistical innovation, marking significant milestones in the field of data analysis and forecasting. The foundational work by Box and Jenkins has established the cornerstone methodology for time series analysis, introducing systematic approaches to model identification through autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis [3]. Their comprehensive framework demonstrated that proper model specification could effectively explain variance in well-behaved time series data, providing practitioners with rigorous statistical foundations for forecasting applications.

The development of systematic approaches to time series analysis through traditional methods created a robust framework for forecasting applications. Hyndman and Athanasopoulos' principles of forecasting established that exponential smoothing methods could effectively capture data patterns when properly specified, with particular strength in decomposing time series into their fundamental components [4]. The framework demonstrated how state space models provide a unified approach to handling various types of exponential smoothing methods, proving especially valuable in business and economic forecasting, where transparent and interpretable results are crucial for decision-making processes.

The Box-Jenkins methodology introduced rigorous diagnostic procedures for model adequacy, emphasizing the importance of residual analysis in model verification [3]. Their systematic approach to model building, encompassing identification, estimation, and diagnostic checking, provided practitioners with a clear framework for developing reliable forecasting models. This methodology established standards for statistical rigor in time series analysis that continue to influence modern approaches.

However, as data complexity increased, the limitations of classical approaches became increasingly apparent. Traditional methods struggled with multiple seasonal patterns, non-linear relationships, and high-dimensional feature spaces that characterize modern datasets [4]. The framework emphasized the importance of selecting appropriate methods based on the characteristics of the time series, introducing systematic approaches to method selection through features such as trend, seasonality, and cyclic patterns. This understanding led to the development of more sophisticated approaches that could handle the increasing complexity of modern time series data.

3. Modern Neural Architectures

Contemporary approaches to time series analysis have been revolutionized by sophisticated neural network architectures specifically designed for temporal data. The advancement from traditional methods to deep learning architectures has shown significant improvements in handling complex temporal patterns. Research has demonstrated that LSTM networks, when properly configured, can effectively process sequences of varying lengths while maintaining stable performance across different domains [5]. These architectures have proven particularly effective in scenarios involving multiple seasonality patterns and long-term dependencies, where traditional approaches often struggle to maintain consistent performance.

The evolution from basic RNNs to more sophisticated architectures like LSTM and GRU networks represents a significant advancement in temporal data processing capabilities. These modern architectures have demonstrated superior ability in capturing complex patterns while addressing fundamental challenges like the vanishing gradient problem. The comparison of different architectural approaches has shown that while LSTMs excel at capturing long-term dependencies, GRU networks often achieve comparable performance with a more streamlined architecture, making them particularly suitable for applications where computational efficiency is crucial [5].The introduction of Temporal Fusion Transformers (TFT) has marked a revolutionary step in time series forecasting. TFTs have demonstrated superior performance compared to state-of-the-art baseline models across multiple datasets, including electricity, traffic, and retail domains [6]. The architecture's innovative approach to variable selection and attention mechanisms allows for effective processing of multi-horizon forecasting tasks while providing interpretable insights into model decisions. When evaluated on complex datasets, TFT architectures have maintained consistent performance across different forecast horizons, demonstrating robust capability in handling diverse temporal patterns.

The advancement in attention mechanisms has particularly enhanced the interpretability and efficiency of time series modeling. Research has shown that TFT models can effectively process multi-horizon forecasting tasks while providing interpretable variable selection patterns [6]. The architecture's ability to automatically identify and utilize relevant input features through learned variable selection weights has proven particularly valuable in real-world applications where understanding model decisions is crucial for practical implementation and stakeholder confidence.

4. Comparative Analysis: Classical vs. Deep Learning Approaches

A comprehensive comparison between classical and deep learning approaches reveals distinctive characteristics in their application to time series forecasting. Research examining large-scale forecasting competitions has demonstrated that hybrid methods combining statistical and machine learning approaches often achieve superior performance compared to standalone methodologies [7]. The analysis shows that while pure statistical methods excel in handling seasonal patterns with well-defined structures, deep learning approaches demonstrate superior capability in capturing complex nonlinear relationships across varying time horizons.

The evolution of forecasting methodologies has highlighted significant differences in computational requirements and practical implementations. Statistical methods have consistently shown advantages in scenarios with limited data availability, often requiring only hundreds of observations for effective model training [8]. In contrast, deep learning approaches typically require substantially larger datasets to achieve optimal results, with successful implementations often utilizing thousands of observations for model training. This fundamental difference in data requirements has significant implications for practical applications, particularly in domains where historical data may be limited or expensive to obtain.

The question of interpretability presents another crucial dimension for comparison in forecasting methodologies. Classical statistical methods maintain a clear advantage in model interpretability, with their mathematical foundations providing transparent relationships between inputs and outputs [7]. While deep learning models may achieve superior accuracy in complex scenarios, their interpretability remains a challenge, though recent advances in explainable AI have begun to bridge this gap. This trade-off between accuracy and interpretability continues to influence method selection in practical applications, particularly in regulated industries where model decisions must be explainable.

The adaptability and scalability of different forecasting approaches have emerged as key differentiating factors in real-world applications. Deep learning methods demonstrate particular strength in handling multiple parallel time series and incorporating external variables, while statistical methods often excel in providing reliable forecasts for individual series with clear patterns [8]. The analysis indicates that the choice between approaches often depends on the specific characteristics of the forecasting problem, including data availability, computational resources, and the need for model interpretability. This understanding has led to an increasing trend toward hybrid approaches that leverage the strengths of both methodological families.

5. Handling Multi-dimensional Time Series

The analysis of multi-dimensional time series has become increasingly critical in modern forecasting applications, particularly with the growing complexity of data relationships. Research analyzing high-dimensional time series has demonstrated that graph neural networks (GNNs) can effectively capture spatial-temporal dependencies in multivariate scenarios. Advanced spatial-temporal graph neural networks have shown the ability to capture complex dependencies effectively, particularly when applied to traffic forecasting, where spatial relationships between monitoring points are crucial [9]. The study highlighted the importance of incorporating spatial-temporal attention mechanisms, which have improved prediction accuracy compared to baseline models that do not consider spatial relationships.

The challenge of handling varying scales and relationships in multi-dimensional time series has been addressed through innovative methodological developments in entropy-based approaches. Comprehensive studies examining multivariate time series data using multiscale entropy analysis have demonstrated significant improvements in capturing complex system dynamics [10]. When applied to financial time series, entropy-based methods have shown utility in analyzing complexity and identifying different dynamic states across various time scales, indicating robust performance across different sampling frequencies. The research revealed that these methods were particularly effective in identifying critical transition points in market behavior.

Incorporating domain-specific knowledge and constraints has emerged as a crucial factor in enhancing multi-dimensional time series analysis.

Studies implementing spatial-temporal graph neural networks have shown that modeling the inherent network topology is crucial for effectively capturing complex spatial-temporal dependencies [9]. The research demonstrated that domain-aware architectures could effectively process data from multiple interconnected sources while maintaining computational efficiency, proving particularly valuable in transportation and infrastructure monitoring applications.

The effective processing of high-dimensional feature spaces remains a fundamental challenge in multivariate time series analysis. Research applying multiscale entropy methods to complex datasets has shown that these approaches can effectively distinguish between different dynamic states in the system [10]. When applied to financial time series, multiscale entropy methods have demonstrated the ability to distinguish different market behaviors and complexity patterns across various time scales. This advance in handling high-dimensional spaces has proven particularly valuable in applications requiring real-time analysis and decision-making.

6. Future Directions in Time Series Analysis

The evolution of time series analysis continues to advance through several transformative directions, with hybrid approaches emerging as a particularly promising avenue. Comprehensive reviews of modern forecasting techniques have demonstrated that hybrid models combining traditional statistical methods with deep learning approaches show significant potential for improving forecast accuracy across diverse domains [11]. These hybrid approaches have shown particular strength in their ability to leverage the interpretability of statistical methods while harnessing the pattern-recognition capabilities of deep learning, leading to more robust and reliable forecasting systems that can adapt to changing data patterns while maintaining interpretable outputs.

The emergence of Automated Machine Learning (AutoML) represents another significant advancement in time series forecasting methodology. AutoML systems have demonstrated remarkable capabilities in automating the end-to-end process of model development, from feature selection through to hyperparameter optimization [12]. The automated approaches have shown particular promise in handling multiple seasonality patterns and complex temporal dependencies, while significantly reducing the time and expertise required for model development. These systems have proven especially valuable in business forecasting scenarios, where they can rapidly adapt to changing patterns while maintaining consistent performance across various time horizons.

The development of explainable AI techniques has become increasingly crucial as time series models grow in complexity. Research has shown that modern interpretation techniques can effectively bridge the gap between complex model architectures and practical business understanding [11]. These advances in explainability have proven particularly valuable in regulated industries where model decisions must be transparent and justifiable.

The integration of domain knowledge with artificial intelligence has emerged as a key factor in developing more reliable and trustworthy forecasting systems that can be effectively deployed in real-world applications.

The future landscape of time series analysis is increasingly shaped by the integration of various methodological approaches. The combination of traditional statistical methods with modern machine learning techniques, enhanced by automated optimization and explainable AI frameworks, has created new opportunities for more sophisticated and reliable forecasting systems [12]. This integration has enabled the development of more adaptable and robust forecasting solutions that can handle the increasing complexity of modern time series data while maintaining interpretability and practical utility.

Table 1: *Machine Learning vs Traditional Methods Comparison [1,2]*

Aspect	Traditional Statistical Methods	Machine Learning Methods
Pattern Recognition	Linear relationships, clear seasonal patterns	Complex non-linear dynamics, irregular patterns
Data Requirements	Moderate, structured historical data	Large datasets, diverse feature sets
Model Selection	Manual identification using ACF/PACF	Automated architecture search, evolutionary approaches
Handling Outliers	Sensitive to anomalies	Robust outlier detection and handling
Adaptability	Static model parameters	Dynamic adaptation to non-stationary data

Best Use Cases	Well-behaved series with clear structure	Multivariate, complex temporal dependencies

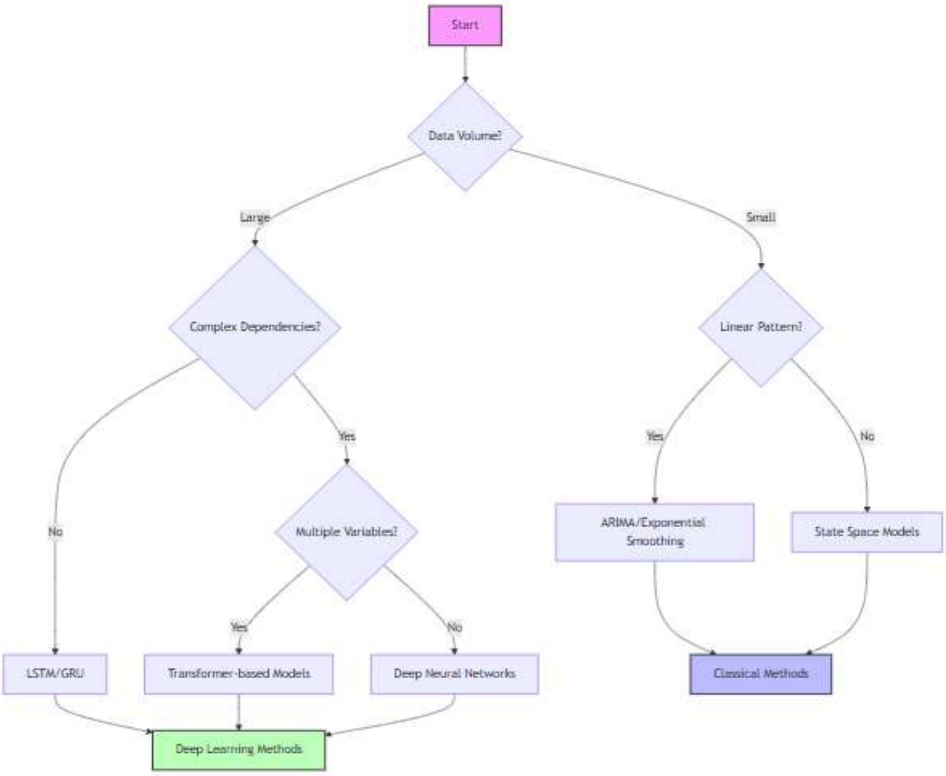

Figure 1: *Time series method selection decision tree*

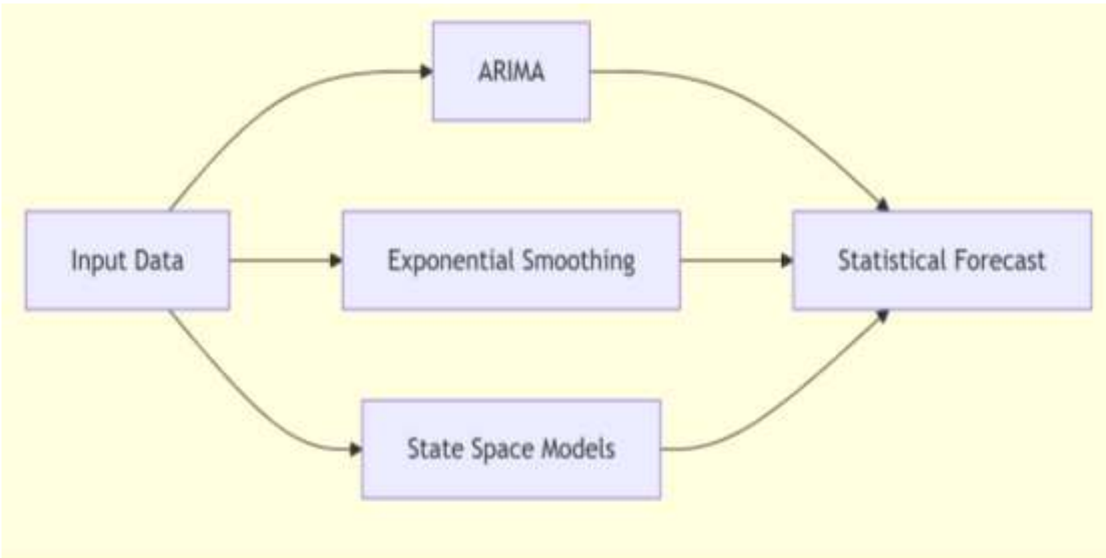

Figure 2*: Classical Methods*

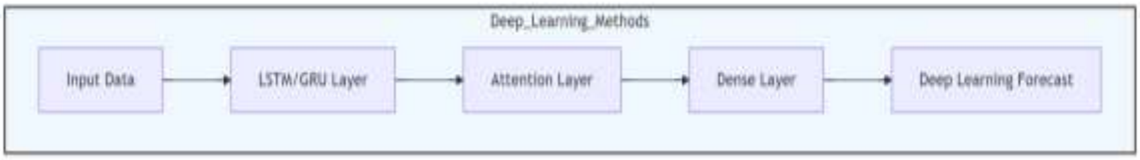

Figure 3: *Deep Learning Methods*

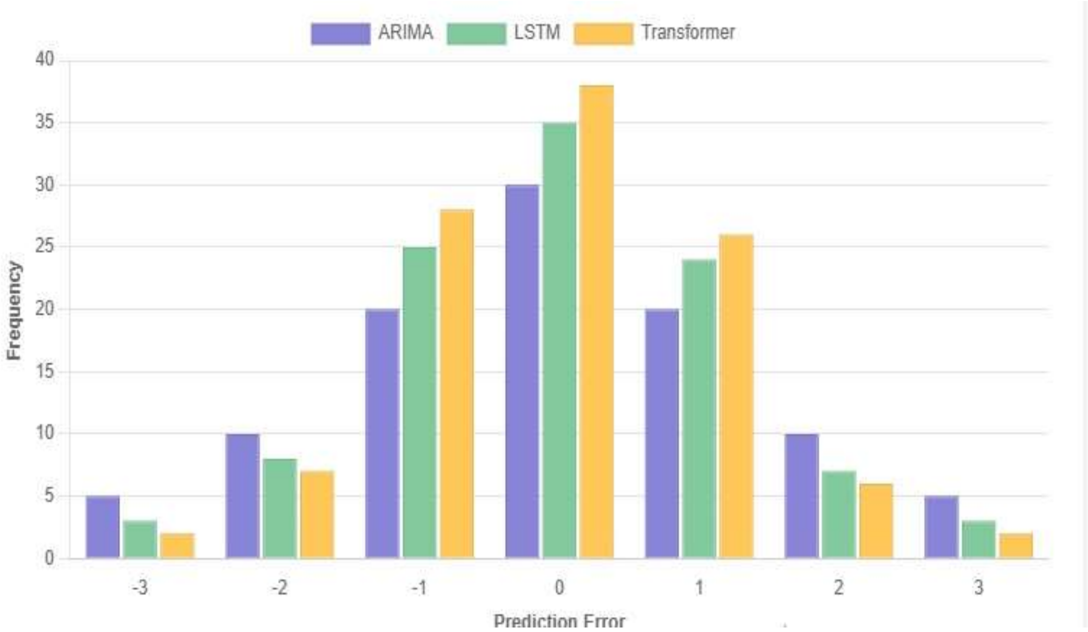

Figure 4: *Error distribution across model types*

Table 2: *Modern Neural Architecture Characteristics [5,6]*

Architecture	Temporal Modeling	Key Innovation	Interpretability	Computational Efficiency
LSTM Networks	Long-term memory cells	Gating mechanisms	Low	Moderate
GRU Networks	Simplified gating	Streamlined architecture	Low	High
Temporal Fusion Transformers	Multi-horizon attention	Variable selection, interpretable attention	High	Moderate
Attention Mechanisms	Context-aware processing	Self-attention, positional encoding	High	Variable
Transformer Models	Parallel sequence processing	Multi-head attention, encoder-decoder	Medium	Low for long sequences

Figure 5: *Comparative forecast performance*

Table 3: *Methodological Paradigm Comparison [7,8]*

Evaluation Criteria	Statistical Methods	Deep Learning	Hybrid Approaches

		Methods	
Model Transparency	High interpretability	Black-box complexity	Balanced interpretability
Training Data Needs	Limited historical data sufficient	Extensive datasets required	Moderate data requirements
Seasonal Handling	Excellent for regular patterns	Superior for complex seasonality	Adaptive seasonal modeling
Computational Demand	Low resource requirements	High computational intensity	Moderate resource usage
Scalability	Limited parallel processing	Excellent multi-series handling	Flexible scaling options
Real-world Deployment	Established business practices	Emerging enterprise adoption	Growing practical implementation

Table 4: *Multi-dimensional Analysis Approaches [9,10]*

Analysis Method	Spatial Relationships	Temporal Dependencies	Application Domain	Key Advantage
Graph Neural Networks	Explicit topology modeling	Convolutional temporal processing	Traffic forecasting	Network structure awareness
Spatio-Temporal Convolution	Grid-based spatial patterns	Localized temporal filters	Urban planning	Computational efficiency
Multiscale Entropy Analysis	Cross-variable interactions	Multi-timescale complexity	Financial markets	Regime change detection
Dynamic System Modeling	State-space relationships	Non-linear temporal evolution	Economic systems	Theoretical foundation
Network-based Forecasting	Node interdependencies	Propagation dynamics	Infrastructure monitoring	Cascading effect modeling

7. Conclusions

The transformation of time series forecasting represents a convergence of statistical principles and artificial intelligence innovations, where the integration of traditional methods with modern neural architectures has created more robust and adaptable solutions for complex forecasting challenges. As the field continues to evolve, the focus remains on developing hybrid approaches that combine the interpretability of statistical methods with the pattern recognition capabilities of deep learning, leading to more sophisticated and reliable forecasting systems that leverage the continued advancement of computational capabilities and architectural innovations to enhance accuracy and applicability across diverse domains. This evolution marks a significant shift in how temporal data is processed and understood, opening new possibilities for predictive analytics in fields ranging from finance to healthcare, while the emergence of automated machine learning platforms has democratized access to advanced forecasting techniques, and developments in explainable AI ensure that complex models remain interpretable and trustworthy. The fusion of domain expertise with artificial intelligence capabilities enables more nuanced and context-aware predictions, particularly valuable in scenarios involving multiple seasonality patterns and intricate dependencies, positioning the field for continued innovation with emerging technologies that promise even greater advances in handling uncertainty, adapting to changing patterns, and providing real-time insights across an expanding range of applications, all while maintaining the growing emphasis on sustainable and ethical AI practices that shape the development of forecasting systems that are not only powerful but also responsible and transparent in their operation. AI is applied to different fields and reported in the literature [13-28].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] Nesreen K. Ahmed, Amir F. Atiya, "An Empirical Comparison of Machine Learning Models for Time Series Forecasting," Taylor & Francis Online, 2010. Available: https://www.tandfonline.com/doi/full/10.1080/07474938.2010.481556

[2] Zimeng Lyu, Alexander Ororbia, Travis Desell, "Online evolutionary neural architecture search for multivariate non-stationary time series forecasting," ScienceDirect, 2023. Available: https://www.sciencedirect.com/science/article/abs/pii/S1568494623005409

[3] Granville Tunnicliffe Wilson, "Time Series Analysis: Forecasting and Control,5th Edition, by George E. P. Box, Gwilym M. Jenkins, Gregory C. Reinsel, and Greta M. Ljung, 2015. Published by John Wiley and Sons, Inc., Hoboken, New Jersey, pp. 712. ISBN: 978-1-118-67502-1" ResearchGate, 2016, Available: https://www.researchgate.net/publication/299459188_Time_Series_Analysis_Forecasting_and_Control_5th_Edition_by_George_E_P_Box_Gwilym_M_Jenkins_Gregory_C_Reinsel_and_Greta_M_Ljung_2015_Published_by_John_Wiley_and_Sons_Inc_Hoboken_New_Jersey_pp_712_ISBN_

[4] Rob J Hyndman and George Athanasopoulos, "Forecasting: principles and practice – A comprehensive introduction to the latest forecasting methods using R," Exploring Economics, 2018. Available: https://www.exploring-economics.org/de/studieren/buecher/forecasting-principles-and-practice/

[5] Achala Edirisooriya, et al., "Deep Learning Architectures for Time Series Forecasting," ResearchGate, 2024. Available: https://www.researchgate.net/publication/385108313_Deep_Learning_Architectures_for_Time_Series_Forecasting

[6] Bryan Lim, et al., "Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting," ScienceDirect, 2020. Available: https://www.sciencedirect.com/science/article/pii/S0169207021000637

[7] Bryan Lim, Stefan Zohren, "Time Series Forecasting With Deep Learning: A Survey, " arxiv, 2020. Available: https://arxiv.org/abs/2004.13408

[8] Evangelos Spiliotis, "Time Series Forecasting with Statistical, Machine Learning, and Deep Learning Methods: Past, Present, and Future," ResearchGate, 2023. Available: https://www.researchgate.net/publication/374080047_Time_Series_Forecasting_with_Statistical_Machine_Learning_and_Deep_Learning_Methods_Past_Present_and_Future

[9] Bing Yu, et al., "Spatio-Temporal Graph Convolutional Networks: A Deep Learning Framework for Traffic Forecasting," IJCAI, 2014-2015. Available: https://www.ijcai.org/proceedings/2018/0505.pdf

[10] Madalena Costa, et al., "Multiscale entropy analysis of biological signals," Physical Review Journals, 2005. Available: https://journals.aps.org/pre/abstract/10.1103/PhysRevE.71.021906

[11] Milind Kolambe, "Forecasting the Future: A Comprehensive Review of Time Series Prediction Techniques," ResearchGate, 2024. Available: https://www.researchgate.net/publication/379671801_Forecasting_the_Future_A_Comprehensive_Review_of_Time_Series_Prediction_Techniques

[12] George Westergaard, et al., “Time Series Forecasting Utilizing Automated Machine Learning (AutoML): A Comparative Analysis Study on Diverse Datasets,” MDPI, 2024. https://www.mdpi.com/2078-2489/15/1/39

[13]García, R. (2025). Optimization in the Geometric Design of Solar Collectors Using Generative AI Models (GANs). International Journal of Applied Sciences and Radiation Research , 2(1). https://doi.org/10.22399/ijasrar.32

[14]Fabiano de Abreu Agrela Rodrigues, & Flávio Henrique dos Santos Nascimento. (2025). Neurobiology of perfectionism. International Journal of Sustainable Science and Technology, 3(1). https://doi.org/10.22399/ijsusat.6

[15]Nadya Vázquez Segura, Felipe de Jesús Vilchis Mora, García Lirios, C., Enrique Martínez Muñoz, Paulette Valenzuela Rincón, Jorge Hernández Valdés, … Oscar Igor Carreón Valencia. (2025). The Declaration of Helsinki: Advancing the Evolution of Ethics in Medical Research within the Framework of the Sustainable Development Goals. International Journal of Natural-Applied Sciences and Engineering, 3(1). https://doi.org/10.22399/ijnasen.26

[16] García, R., Carlos Garzon, & Juan Estrella. (2025). Generative Artificial Intelligence to Optimize Lifting Lugs: Weight Reduction and Sustainability in AISI 304 Steel. International Journal of Applied Sciences and Radiation Research , 2(1). https://doi.org/10.22399/ijasrar.22

[17] Attia Hussien Gomaa. (2025). From TQM to TQM 4.0: A Digital Framework for Advancing Quality Excellence through Industry 4.0 Technologies. International Journal of Natural-Applied Sciences and Engineering, 3(1). https://doi.org/10.22399/ijnasen.21

[18] Kumari, S. (2025). Machine Learning Applications in Cryptocurrency: Detection, Prediction, and

Behavioral Analysis of Bitcoin Market and Scam Activities in the USA. International Journal of Sustainable Science and Technology, 3(1). https://doi.org/10.22399/ijsusat.8

[19]Ibeh, C. V., & Adegbola, A. (2025). AI and Machine Learning for Sustainable Energy: Predictive Modelling, Optimization and Socioeconomic Impact In The USA. International Journal of Applied Sciences and Radiation Research , 2(1). https://doi.org/10.22399/ijasrar.19

[20] Soyal, H., & Canpolat, M. (2025). Intersections of Ergonomics and Radiation Safety in Interventional Radiology. International Journal of Sustainable Science and Technology, 3(1). https://doi.org/10.22399/ijsusat.12

[21]Olola, T. M., & Olatunde, T. I. (2025). Artificial Intelligence in Financial and Supply Chain Optimization: Predictive Analytics for Business Growth and Market Stability in The USA. International Journal of Applied Sciences and Radiation Research , 2(1). https://doi.org/10.22399/ijasrar.18

[22]Vishwanath Pradeep Bodduluri. (2025). Social Media Addiction and Its Overlay with Mental Disorders: A Neurobiological Approach to the Brain Subregions Involved. International Journal of Sustainable Science and Technology, 3(1). https://doi.org/10.22399/ijsusat.3

[23]Harsha Patil, Vikas Mahandule, Rutuja Katale, & Shamal Ambalkar. (2025). Leveraging Machine Learning Analytics for Intelligent Transport System Optimization in Smart Cities. International Journal of Applied Sciences and Radiation Research , 2(1). https://doi.org/10.22399/ijasrar.38

[24]García Lirios, C., Jose Alfonso Aguilar Fuentes, & Gabriel Pérez Crisanto. (2025). Theories of Information and Communication in the face of risks from 1948 to 2024. International Journal of Natural-Applied Sciences and Engineering, 3(1). https://doi.org/10.22399/ijnasen.19

[25] Attia Hussien Gomaa. (2025). Value Engineering in the Era of Industry 4.0 (VE 4.0): A Comprehensive Review, Gap Analysis, and Strategic Framework. International Journal of Natural-Applied Sciences and Engineering, 3(1). https://doi.org/10.22399/ijnasen.22

[26]Fabiano de Abreu Agrela Rodrigues, Flavio Henrique dos Santos Nascimento, André Di Francesco Longo, & Adriel Pereira da Silva. (2025). Genetic study of gifted individuals reveals individual variation in genetic contribution to intelligence. International Journal of Applied Sciences and Radiation Research , 2(1). https://doi.org/10.22399/ijasrar.25

[27] Chui, K. T. (2025). Artificial Intelligence in Energy Sustainability: Predicting, Analyzing, and Optimizing Consumption Trends. International Journal of Sustainable Science and Technology, 3(1). https://doi.org/10.22399/ijsusat.1

[28]Fabiano de Abreu Agrela Rodrigues. (2025). Related Hormonal Deficiencies and Their Association with Neurodegenerative Diseases. International Journal of Sustainable Science and Technology, 3(1). https://doi.org/10.22399/ijsusat.5