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Predictive Analytics for Demand Forecasting: A deep Learning-based Decision Support

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Abstract

Demand forecasting is a critical component of supply chain management and business operations, enabling organizations to make informed decisions about production, inventory management, and resource allocation. In recent years, predictive analytics has emerged as a powerful tool for enhancing the accuracy and efficiency of demand forecasting. This review paper explores the transformative role of predictive analytics and deep learning in demand forecasting. It examines how these advanced techniques have evolved from traditional models based on past sales data, offering nuanced predictions through sophisticated statistical and machine learning methods. Deep learning, with its neural network structures, brings automatic feature learning, complex pattern handling, and scalability, enhancing forecasting in sectors like retail, manufacturing, and healthcare. The paper reviews various deep learning models, compares them with traditional methods, and discusses their impact on business operations and decision-making. It concludes by looking at future trends in predictive analytics and deep learning in demand forecasting.

Keywords: Demand forecasting Predictive analytics Deep learning Optimization Demand sensing Retail

1. Introduction

Understanding and anticipating market demand is essential for the vitality and growth of any business. This process, known as demand forecasting, plays a pivotal role in strategic decision-making, guiding companies in production planning, inventory control, and logistical operations. In the past, firms relied heavily on past sales data and linear forecasting models; however, the introduction and integration of predictive analytics have revolutionized this practice [9]. Predictive analytics incorporates a variety of statistical techniques, including machine learning algorithms, to interpret data and identify patterns. This approach allows for more nuanced predictions based on a wide array of variables, such as market trends, consumer Behaviour, and economic indicators [37]. Demand prediction is a cornerstone for success across multiple sectors like retail, manufacturing, the supply chain, and healthcare. For example, precise predictions of demand lead to numerous benefits, such as streamlined inventory, cost reduction, and enhanced customer contentment. Retailers, for instance, rely on demand insights to keep their inventory balanced and avoid excess or shortage. Manufacturers utilize forecasts to streamline their production processes, thereby curbing unnecessary expenses and waste. In the healthcare industry, projecting the number of patient admissions assists in the proper distribution of resources, guaranteeing that hospitals have sufficient staff and equipment to provide for patient care [3]-[5]. Demand forecasting involves predicting the quantity of a product that consumers will purchase during a specific time period. This process is critical for sellers to optimize space, time, and financial resources [6]. Effective demand forecasting helps in managing inventory by predicting product needs accurately, thus avoiding surplus and minimizing storage costs. The complexity of demand forecasting increases with the number of influencing factors such as price, popularity, seasonal trends, and market dynamics. Inaccurate demand predictions can lead to either surplus inventory, if the actual demand is lower than expected, or lost revenue and customer dissatisfaction, if the demand exceeds the supply. The goal is to enhance predictive accuracy and efficiency, thereby maximizing revenue and reducing operational costs [16]. Current efforts emphasize the development of artificial intelligence (AI)-based forecasting methods that leverage big data, given the urgent need for rapid and effective decision-making in emergencies. Historically, AI research has pursued two main paths:

- Traditional Approach: This involves simulating the human brain to create AI systems, integrating insights f rom computer science, psychology, and neuroscience. Neural networks, a product of this approach, were initially used for emergency material demand prediction but were limited by their simplistic models.
- Modern Approach: Focuses on utilizing the computational precision and data handling capabilities of machines, particularly through machine learning and deep learning, which are better suited to managing large volumes of data and complex problem-solving scenarios.

These AI-driven methods are crucial for developing resilient forecasting systems that can adequately predict the demand for emergency resources and improve overall disaster response effectiveness. Machine learning models, particularly those developed through supervised learning and unsupervised learning, are proving to be more effective than traditional models used in supply chain management [8]-[12]. These models apply various algorithmic approaches, including neural networks, support vector machines, decision trees, and k-means clustering, each suitable for specific tasks like regression, classification, clustering, and association. Recent applications of machine learning in supply chain management show promising results in improving demand forecasting models, thereby enhancing overall supply chain efficiency and reducing costs [7]. The use of machine learning not only helps in accurately predicting demand but also in adapting to new patterns as they emerge, making it a critical tool in modern supply chain operations. **The remaining parts of the paper are put together in the following manner: In the section 2, the related work using deep learning is presented, and in the section 3, the literature review is discussed. In section 4 different applications are discussed. The challenges and forecasting are discussed in section 5.**

2. Deep Learning: A Paradigm Shift in Demand Forecasting

The visualization in Fig 1 demonstrates how predictive analytics can be applied to demand forecasting. The purpose of this discourse is to delve into the realm of predictive analytics as applied to demand forecasting.

Deep learning has emerged as a groundbreaking force in enhancing the capabilities of demand forecasting. Mimicking the complexity of the human brain, it employs layered structures of artificial neural networks to analyze and learn from data [9]. This method unveils a plethora of benefits that are especially fitting for tackling the complexities inherent in contemporary demand forecasting tasks:

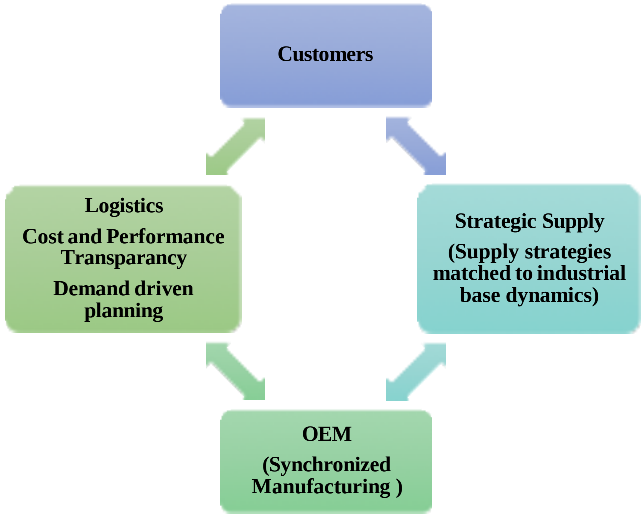

Fig 1. Predictive analytics for demand forecasting

- Automatic Feature Learning: Deep learning models are adept at discerning important data characteristics without human intervention, streamlining the process particularly when confronted with large, unstructured datasets.
- Handling Complexity: Standard linear approaches fall short in scenarios where demand patterns are highly intricate. Deep learning frameworks are particularly proficient at navigating these non- l inear interdependencies.
- Time Series Insights: Deep learning approaches are adept at recognizing complex patterns over time, an essential feature for forecasting future demand where past trends often influence outcomes.
- Growth with Data: The architecture of deep learning models is designed to manage and learn from extensive datasets, an invaluable trait in

environments flush with data.

- Deep Learning Techniques for Demand Forecasting
- Several deep learning techniques have found practical application in demand forecasting:
- Recurrent Neural Networks (RNNs): These networks are well-suited for time series forecasting, as they can capture sequential dependencies. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are popular RNN variants that excel in capturing temporal patterns.
- Convolutional Neural Networks (CNNs): While typically associated with image processing, CNNs have also been applied to demand forecasting. They can analyze patterns and spatial dependencies in data.
- Deep Feedforward Neural Networks: These are multi- layer perceptron that can model complex relationships within data. They are used for demand forecasting when historical data is essential but not in a time series format
- Deep learning has yielded a variety of approaches valuable for enhancing demand forecasting:
- Sequential Analysis Networks: Networks like Recurrent Neural Networks (RNNs) are adept at analyzing data where order matters, making them fitting for forecasting based on time series data. Subsets such as Long Short-Term Memory (LSTM) units and Gated Recurrent Units (GRUs) specialize in identifying and retaining information over extended periods, which is critical for recognizing trends over time.
- Pattern Recognition Networks: Convolutional Neural Networks (CNNs) are renowned for their image recognition capabilities, but they've also proven useful in demand forecasting for their ability to detect patterns and correlations in data that might not be immediately adjacent.
- Multilayer Perceptron Networks: Deep Feedforward Neural Networks, a kind of multilayer perceptron, are effective at deciphering complex data interrelations. These networks are particularly beneficial for demand forecasting tasks where chronological order is less pertinent, but the historical context remains crucial.

3. Literature Review

Wan et al.[13] Wan et al.'s study evaluates and contrasts traditional forecasting models with newer technologies for both perishable and non-perishable products. The comparison focuses on several key aspects: the accuracy of predictions, the models' ability to generalize, the time they take to run, their cost-effectiveness, and their ease of use for businesses.

Mohamad et al.[2] proposes two encoder-decoder models using convolutional and bidirectional ConvLSTM combined with a standard LSTM network to extract key features from energy demand data of EVCS, comparing their outcomes with conventional models.

Parizad et al.[17] utilize the TensorFlow framework within a Python environment, executed on a high- performance computing cluster, to refine the hyperparameters of Deep Neural Networks (DNNs). This process aims to develop a robust and precise model for predicting load demands.

Chen et al.[14] introduced a three-stage hierarchical demand forecasting model tailored for perishable goods production. This model outperformed the industry- standard model, reducing lost profits by 1.71% and decreasing total sales by 3.30%.

Sukla et al.[19] created a day-ahead load forecasting model using Convolutional Neural Networks (CNNs). This model is specifically designed to analyze time series load data and incorporate weather information. The model's performance was enhanced through k-cross validation, and its accuracy was assessed using metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Additionally, it was compared to an Artificial Neural Networks (ANN) model.

Badorf et al.[6] designed a random coefficient model that uncovered the intricate influence of weather conditions on daily sales. Their analysis revealed that the impact of weather varies significantly depending on the store's location and the type of products being sold. This impact ranged from 23.1% to 40.7%, indicating a diverse and nuanced relationship between weather and sales.

Thomassey et al.[6] introduce various forecasting models aimed at improving the accuracy and reliability of sales forecasts. These models leverage advanced techniques, including fuzzy logic, neural networks, and data mining. To assess the advantages of these methods in supply chain management, particularly in mitigating the bullwhip effect, the researchers conducted a simulation using real data from sourcing and forecasting processes, followed by a thorough analysis of the results.

Punia, et al.[15] introduce an innovative forecasting approach that integrates deep learning techniques, specifically LSTM networks, with random forest. This method excels in accurately modeling intricate temporal and regression relationships. Additionally, it ranks explanatory variables based on their significance in the forecasting process.

Geurts, et al.[9] investigate the complexities of adapting forecasting methods to improve the precision of retail sales predictions. Their study emphasizes the influence of factors such as competitor actions, discounts, store promotions, weather conditions, and consumption holidays on sales outcomes.

Ferreira et al.[11] showcase a case study involving Rue La La, an online retailer, where they illustrate the application of data-driven strategies for optimizing pricing decisions. They create an algorithm specifically tailored for multiproduct price optimization, which is then integrated into a pricing decision support tool. The results from a field experiment indicate that this approach leads to a notable increase in revenue, approximately 9.7%, without a decrease in sales.

Choi et al.[2] explore the development of an optimal two- stage ordering policy designed for seasonal products in their research. They present a comprehensive implementation plan and delve into the discussions about service level and profit uncertainty levels achieved through this optimal policy. The study extensively employs numerical analyses to assess the performance and effectiveness of this policy.

Au et al.[12] introduce an evolutionary computation- based method for enhancing a forecasting system using two years' worth of apparel sales data. The neural networks optimized through this approach demonstrate superior performance compared to traditional SARIMA models, particularly in situations with low demand uncertainty and modest seasonal patterns. This method is particularly beneficial for retailers aiming to generate short-term forecasts for apparel items that exhibit these characteristics.

Kumar et al.[7] suggest a novel approach to combine forecasts by applying clustering techniques to identify groups of items with similar sales forecast patterns. Their method surpasses the performance of individual forecasts or a single combined forecast for all items within a retail chain.

Guo et al.[9] introduced a multivariate intelligent decision-making model that exhibits superior performance compared to extreme learning machine-based and generalized linear models when it comes to generating more accurate forecasts within the retail industry.

Pai et al.[14] introduce a hybrid approach that leverages the respective strengths of both the ARIMA model and Support Vector Machines (SVMs) for forecasting stock prices. They validate the accuracy of this model using real stock price datasets and report highly promising results based on computational tests.

Zhang et al.[3] present a hybrid approach that merges ARIMA (AutoRegressive Integrated Moving Average) and ANN (Artificial Neural Network) models to benefit from their respective strengths in linear and nonlinear modeling. Through experiments conducted with real datasets, they demonstrate that this combined model proves to be an effective strategy for enhancing forecasting accuracy compared to using either model individually.

Athanasopoulos et al.[12] introduce the concept of Temporal Hierarchies in the context of time series forecasting. They also explore the organizational implications of aligning forecasts over time using a case study focused on Accident & Emergency departments.

Murray et al.[8] suggest that the influence of weather, especially sunlight, on consumer spending is influenced by negative affect. In other words, as exposure to sunlight increases, negative affect diminishes, leading to an uptick in consumer spending. Their proposal gains substantial backing through a series of three comprehensive studies that encompass both controlled laboratory experiments and real-world field observations.

Shankar et al.[18] introduce an innovative approach for multivariate container throughput forecasting, utilizing Long Short-Term Memory networks (LSTM). The precision of this forecasting method is assessed using an error matrix, and its accuracy is substantiated through the Diebold-Mariano statistical test.

Hu et al.[10] put forth a Memetic Algorithm (MA) based on the firefly algorithm to identify suitable input features from a pool of feature candidates, encompassing time lagged loads and temperatures. They conducted thorough quantitative assessments, and the experimental findings indicate that the suggested MSVR-MA forecasting framework holds promise as an effective approach for interval load forecasting.

Falatouri et al.[20] offer an overview of strategies in retail Supply Chain Management (SCM) and conduct a comparative analysis of two specific methods. Additionally, they evaluated the performance of these methods in comparison to SARIMAX, especially when incorporating the external factor of promotions. Notably, SARIMAX demonstrated superior performance for products with promotions. To enhance forecasting accuracy at the store level, the researchers propose hybrid approaches that involve training SARIMA(X) and LSTM models on similar, pre-clustered store groups.

Bharadiya et al.[38] emphasize that the integration of machine learning and artificial intelligence (AI) into business intelligence holds great promise and presents numerous opportunities. Employing these technologies enables businesses to gain a competitive advantage, foster innovation, and achieve higher levels of success in the digital age.

Ghazal et al.[21] propose an IoT-based smart meter that utilizes deep extreme machine learning and support vector machine for professional energy management. It achieves a high accuracy of 90.70% in predicting power consumption, surpassing previous techniques. It also includes automatic load control for improved efficiency. Mostafa et al.[22] develop a framework for big data analytics in smart grids and renewable energy utilities. They achieve impressive accuracy rates, with 96% accuracy using 70% of the data, 84% accuracy with a random forest tree, 78% accuracy with a decision tree, and 87% accuracy for classification.

Yi et al.[23] present a time-series forecasting model for monthly commercial EV charging demand using a deep learning approach called Sequence to Sequence (Seq2Seq). The model outperforms other models significantly in multi-step predictions, showcasing its proficiency in sequential data predictions.

Kaya et al.[24] propose a hotel demand forecasting model utilizing Attention-Long Short-Term Memory (Attention- LSTM) to predict weekly hotel demand four weeks in advance. The model achieves lower mean absolute error and percentage error compared to existing machine learning and deep learning models, using real-world data from Turkey.

Tsolaki et al.[39] explore the state-of-the-art applications in freight transportation, supply chain, and logistics, focusing on areas such as arrival time prediction, demand forecasting, industrial process optimization, traffic flow analysis, vehicle routing, and anomaly detection in transportation data.

Elot et al.[25] provide an overview of technology advancements and big data analytics in underwater sensors. They discuss the advantages and disadvantages of these sensors and explore new investigative methods in this field.

Rao et al.[26] employ machine learning algorithms, including linear regression, support vector machines, and artificial neural networks (ANN), to predict short-term load demand. They analyze the effectiveness of three optimization techniques and find that the Levenberg- Marquardt optimization algorithm-based ANN model yields the best electrical load forecasting results.

Zu et al.[27] discuss the application of machine learning algorithms in evaluating water quality across various water environments, including surface water, groundwater, drinking water, sewage, and seawater.

Roini et al.[28] explore wireless communication as a rapidly evolving technology in the f ield of communication. They investigate different approaches and their pros and cons regarding underwater sensor networks, aiming to identify future research opportunities.

Fu et al.[29] delve into various aspects of water management, including water demand forecasting, leak detection, sewer defect assessment, wastewater system prediction, asset monitoring, and urban flooding. Their focus is on inspiring research and development in deep learning systems for sustainable water management.

Velasquez et al.[30] analyze three time series approximations for Brazil's electricity demand from 2021 to 2025, with a specific emphasis on historical data baselines and percent error in relation to predictions from the Energy Research Company (EPE). Their findings suggest that the Regression with Seasonality approach yields the best results, and the choice of historical data significantly affects approximation accuracy.

Huan et al.[31] propose a Dynamical Spatial-Temporal Graph Neural Network model (DSTGNN) for traffic demand prediction. DSTGNN involves creating a spatial dependence graph and inferring intensity. Their experiments with real datasets demonstrate that DSTGNN outperforms existing models in traffic demand prediction.

Kalil et al.[40] present a comprehensive review of research publications from 2015 onwards related to data- driven building energy consumption forecasting. They highlight gaps and challenges in this field and suggest promising directions for future research.

Pallonetto et al.[32] compare two short-term load forecasting techniques, Long Short-term Memory Networks (LSTMs) and Support Vector Machines (SVM), and conduct an experiment to investigate the importance of feature selection. Their study applies these models to one-hour and one-day ahead peak and valley load forecasting scenarios.

Ali et al.[33] propose an approach for enhancing the authenticity and effectiveness of the Supply Chain Collaboration Process. They assert that their approach yields more accurate and improved results compared to previous techniques for supply chain collaboration.

Rao et al.[34] estimate the demand for various forms of energy consumption in China. They predict that the demand for oil will have a stable annual growth rate of 3.52%, while natural gas and primary electricity will experience rapid growth, with an annual rate of 8.05%, indicating a shift towards cleaner energy sources.

Chung et al.[35] introduce a CNN-LSTM attention model for heat load and demand forecasting, demonstrating its superior accuracy compared to previous models. This model is expected to be beneficial for Combined Heat and Power (CHP) plant management.

Torres et al.[36] propose a deep neural network, specifically a Long Short-Term Memory (LSTM) network, for short-term electricity consumption forecasting. They compare LSTM to other deep neural networks and traditional machine learning techniques, achieving a prediction error below 1.5%.

4. Applications

Demand forecasting is a vital business practice that finds applications across diverse industries, providing valuable insights for informed decision-making, operational efficiency, and maintaining competitiveness. Here are some key areas where demand forecasting plays a crucial role:

- Retail and E-commerce: Retailers rely on demand forecasting to stock the right products in the right quantities, ensuring they meet customer demand while minimizing overstock or understock situations.
- Manufacturing and Production: Demand forecasting guides production planning, helping manufacturers optimize their processes, reduce waste, and manage resources efficiently.
- Healthcare: Accurate demand forecasts for patient admissions and medical supplies ensure healthcare facilities are adequately staffed and equipped to meet patient needs, improving patient care.
- Energy Management: Demand forecasting assists in managing energy consumption efficiently, helping energy providers balance supply and demand and reduce costs.
- Supply Chain Management: Supply chain professionals use demand forecasts to streamline logistics, minimize inventory holding costs, and ensure timely deliveries to customers.

5. Challenges in Demand Forecasting

Despite the potential of deep learning in demand forecasting, several challenges are observed as presented in Fig 2.

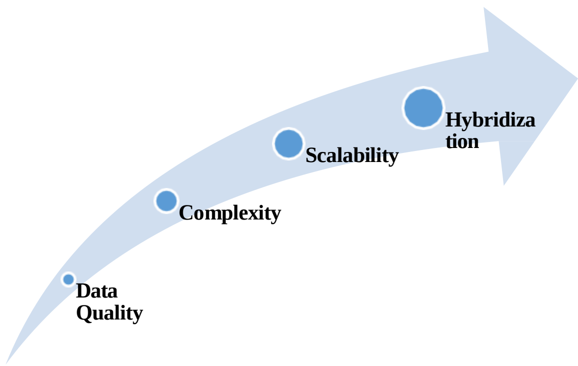

Fig. 2. Current Challenges and Future Scope

Following are some of the challenges that can be explored for future research work:

- As deep learning relies on high-quality and diverse datasets. Therefore, to handle such large amount of data there is need of integration of feature engineering for that.
- Most of the deep learning models used for demand forecasting are "black boxes" in nature and therefore may be computationally intensive.
- While deep learning can handle large datasets, it may require significant computational resources. Scalable solutions are crucial to make these techniques more accessible and cost-effective.
- Combining deep learning with traditional forecasting methods can potentially provide a balance between efficiency and complexity.

6. Conclusion

Deep learning has the potential to transform demand forecasting by overcoming the shortcomings of conventional methods. Its capacity to uncover complex patterns, manage large datasets, and adapt to dynamic market conditions positions it as a revolutionary tool for improving inventory management, resource allocation, pricing strategies, and supply chain efficiency. In the upcoming chapters, we delve deeper into the realm of predictive analytics for demand forecasting using deeplearning, where we explore the methodologies, applications, and real-world success stories that are shaping the future of this dynamic field.

References

1. Geurts, M. D., & Kelly, J. P. (1986). Forecasting retail sales using alternative models. *International Journal of Forecasting*, *2*(3), 261-272.
2. Choi, T. M., Li, D., & Yan, H. (2003). Optimal two- stage ordering policy with Bayesian information updating. *Journal of the operational research society*, *54*(8), 846-859.
3. Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, *50*, 159-175.
4. Pai, P. F., & Lin, C. S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. *Omega*, *33*(6), 497-505.
5. Au, K. F., Choi, T. M., & Yu, Y. (2008). Fashion retail forecasting by evolutionary neural networks. *International Journal of Production Economics*, *114*(2), 615-630.
6. Thomassey, S. (2010). Sales forecasts in clothing industry: The key success factor of the supply chain management. *International Journal of Production Economics*, *128*(2), 470-483.
7. Kumar, M., & Patel, N. R. (2010). Using clustering to improve sales forecasts in retail merchandising. *Annals of Operations Research*, *174*, 33-46.
8. Murray, K. B., Di Muro, F., Finn, A., & Leszczyc, P. P. (2010). The effect of weather on consumer spending. *Journal of Retailing and Consumer Services*, *17*(6), 512-520.
9. Guo, Z. X., Wong, W. K., & Li, M. (2013). A multivariate intelligent decision-making model for retail sales forecasting. *Decision Support Systems*, *55*(1), 247-255.
10. Hu, Z., Bao, Y., Chiong, R., & Xiong, T. (2015). Mid- term interval load forecasting using multi-output support vector regression with a memetic algorithm for feature selection. *Energy*, *84*, 419-431Choi, T. M., Li, D., & Yan, H. (2003). Optimal two-stage ordering policy with Bayesian information updating. *Journal of the operational research society*, *54*(8), 846-859.
11. Ferreira, K. J., Lee, B. H. A., & Simchi-Levi, D. (2016). Analytics for an online retailer: Demand forecasting and price optimization. *Manufacturing & service operations management*, *18*(1), 69-88.
12. Athanasopoulos, G., Hyndman, R. J., Kourentzes, N., & Petropoulos, F. (2017). Forecasting with temporal hierarchies. *European Journal of Operational Research*, *262*(1), 60-74.
13. Wang, J., Liu, G. Q., & Liu, L. (2019, March). A selection of advanced technologies for demand forecasting in the retail industry. In *2019 IEEE 4th International Conference on Big Data Analytics (ICBDA)* (pp. 317-320). IEEE.
14. Chen, C., Wang, Y., Huang, G., & Xiong, H. (2019, December). Hierarchical demand forecasting for factory production of perishable goods. In *2019 IEEE International Conference on Big Data (Big Data)* (pp. 188-193). IEEE.
15. Punia, S., Nikolopoulos, K., Singh, S. P., Madaan, J. K., & Litsiou, K. (2020). Deep learning with long short-term memory networks and random forests for demand forecasting in multi-channel retail. *International journal of production research*, *58*(16), 4964-4979.
16. Badorf, F., & Hoberg, K. (2020). The impact of daily weather on retail sales: An empirical study in brick- and-mortar stores. *Journal of Retailing and Consumer Services*, *52*, 101921.
17. Parizad, A., & Hatziadoniu, C. (2021). Deep learning algorithms and parallel distributed

computing techniques for high-resolution load forecasting applying hyperparameter optimization. *IEEE Systems Journal*, *16*(3), 3758-3769.

18. Shankar, S., Punia, S., & Ilavarasan, P. V. (2021). Deep learning- based container throughput forecasting: A triple bottom line approach. *Industrial Management & Data Systems*, *121*(10), 2100-2117.
19. Shukla, A., & Gupta, A. K. (2022, November). Electric Load Forecasting through CNN: A Deep Learning Approach Considering Weather data. In *2022 IEEE 10th Power India International Conference (PIICON)* (pp. 1-6). IEEE.
20. Falatouri, T., Darbanian, F., Brandtner, P., & Udokwu,

    C. (2022). Predictive analytics for demand forecasting–a comparison of SARIMA and LSTM in retail SCM. *Procedia Computer Science*, *200*, 993-1003.
21. Ghazal, T. M. (2022). Energy demand forecasting using fused machine learning approaches. *Intelligent Automation & Soft Computing*, *31*(1), 539-553.
22. Mostafa, N., Ramadan, H. S. M., & Elfarouk, O. (2022). Renewable energy management in smart grids by using big data analytics and machine learning. *Machine Learning with Applications*, *9*, 100363.
23. Yi, Z., Liu, X. C., Wei, R., Chen, X., & Dai, J.

    (2022). Electric vehicle charging demand forecasting using deep learning model. *Journal of Intelligent Transportation Systems*, *26*(6), 690-703.
24. Kaya, K., Yılmaz, Y., Yaslan, Y., Öğüdücü, Ş. G., & Çıngı, F. (2022). Demand forecasting model using hotel clustering findings for hospitality industry. *Information Processing & Management*, *59*(1), 102816.
25. Gehlot, A., Ansari, B. K., Arora, D., Anandaram, H., Singh, B., & Arias-Gonzáles, J. L. (2022, July). Application of neural network in the prediction models of machine learning based design. In *2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)* (pp. 1-6). IEEE.
26. Rao, S. N. V. B., Yellapragada, V. P. K., Padma, K.,

    Pradeep, D. J., Reddy, C. P., Amir, M., & Refaat, S. S. (2022). Day-ahead load demand forecasting in urban community cluster microgrids using machine learning methods. *Energies*, *15*(17), 6124.
27. Zhu, M., Wang, J., Yang, X., Zhang, Y., Zhang, L., Ren, H., ... & Ye, L. (2022). A review of the application of machine learning in water quality evaluation. *Eco-Environment & Health*, *1*(2), 107-116.
28. Rohini, P., Tripathi, S., Preeti, C. M., Renuka, A., Gonzales, J. L. A., & Gangodkar, D. (2022, April). A study on the adoption of Wireless Communication in Big Data Analytics Using Neural Networks and Deep Learning. In *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 1071-1076). IEEE.
29. Velasquez, C. E., Zocatelli, M., Estanislau, F. B., & Castro, V. F. (2022). Analysis of time series models for Brazilian electricity demand forecasting. *Energy*, *247*, 123483.
30. N. Ali et al., "Fusion-based supply chain collaboration using machine learning techniques," Intell. Autom. Soft Comput., vol. 31, no. 3, pp. 1671– 1687, 2022, doi: 10.32604/IASC.2022.019892.
31. Pallonetto, F., Jin, C., & Mangina, E. (2022). Forecast electricity demand in commercial building with machine learning models to enable demand response programs. *Energy and AI*, *7*, 100121.
32. Chung, W. H., Gu, Y. H., & Yoo, S. J. (2022). District heater load forecasting based on machine learning and parallel CNN-LSTM attention. *Energy*, *246*, 123350.
33. Fu, G., Jin, Y., Sun, S., Yuan, Z., & Butler, D. (2022).

    The role of deep learning in urban water management: A critical review. *Water Research*, *223*, 118973.
34. Huang, F., Yi, P., Wang, J., Li, M., Peng, J., & Xiong,

    X. (2022). A dynamical spatial-temporal graph neural network for traffic demand prediction. *Information Sciences*, *594*, 286-304.
35. Khalil, M., McGough, A. S., Pourmirza, Z.,

Pazhoohesh, M., & Walker, S. (2022). Machine Learning, Deep Learning and Statistical Analysis for forecasting building energy consumption—A systematic review. *Engineering Applications of Artificial Intelligence*, *115*, 105287.

36. Torres, J. F., Martínez-Álvarez, F., & Troncoso, A. (2022). A deep LSTM network for the Spanish electricity consumption forecasting. *Neural Computing and Applications*, *34*(13), 10533-10545.

37. Mohammad, F., Kang, D. K., Ahmed, M. A., & Kim,

Y. C. (2023). Energy demand load forecasting for electric vehicle charging stations network based on ConvLSTM and BiConvLSTM architectures. *IEEE Access*.

38. Bharadiya, J. P. (2023). Machine learning and AI in business intelligence: Trends and opportunities. *International Journal of Computer (IJC)*, *48*(1), 123-134.

39. Tsolaki, K., Vafeiadis, T., Nizamis, A., Ioannidis, D., & Tzovaras, D. (2023). Utilizing machine learning on freight transportation and logistics applications: A review. *ICT Express*, *9*(3), 284-295.

40. Rao, C., Zhang, Y., Wen, J., Xiao, X., & Goh, M. (2023). Energy demand forecasting in China: A support vector regression-compositional data second exponential smoothing model. *Energy*, *263*, 125955.