Review Article

A Comprehensive Review of Statistical and Machine Learning Based Forecasting Techniques and its Application Domains

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Abstract: Machine learning techniques have become pivotal in revolutionizing various industries, offering transformative solutions to complex challenges. This review paper provides an extensive examination of the multifaceted applications of machine learning across diverse sectors. It explores how machine learning is reshaping industries including accommodation, tourism, manufacturing, supply chain, energy and utilities, transportation and logistics, water management and environment, retail and hospitality, pharmaceutical and healthcare, and technology and innovation. This research delves into specific use cases within each industry, highlighting the unique ways in which machine learning is employed to optimize processes, enhance decision-making, and drive innovation. From predicting demand patterns in the hospitality sector to optimizing manufacturing processes through predictive maintenance, machine learning has demonstrated its capacity to deliver tangible benefits. Furthermore, the review discusses the challenges and opportunities associated with integrating machine learning into these sectors, addressing issues related to data privacy, scalability, and ethical considerations. This comprehensive review aims to provide researchers, practitioners, and policymakers with valuable insights into the dynamic landscape of machine learning applications across a wide array of industries, fostering a deeper understanding of its potential and impact on modern business and society.

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Introduction

Artificial intelligence (AI) as it is commonly known is a composite technology of which machine learning is one of the most critical ones. It is a versatile tool favored for decision-making and forecasting, and those qualities have made it a revolutionary tool in today's world. This review paper focuses on the analysis of how machine learning is transforming industries as different as accommodation and tourism, manufacturing and supply chain, energy and utilities, transport and logistics, water management and environment, retail and hospitality, pharmaceutical and healthcare, and technology and innovation.

In the recent past, these industries have been able to apply machine learning thus providing solutions to challenging issues and more prominently recording high-scale growth and progress. For instance, in the accommodation and tourism industry, machine learning is used to tailor the customer relationship, customizes the prices and recommendations of the destination. The paper (Law *et al*., 2019) provides a comprehensive meta-analysis of two decades of tourism demand forecasting literature to address the current knowledge gaps and contribute to the predictive accuracy improvement in line with the increased usage of big data and machine learning techniques among researchers and industry stakeholders.

According to (Aamer *et al*., 2020), the manufacturing and supply chain business has benefited from machine learning in its operations through, prediction of equipment maintenance and the forecasting of the demand all of which have helped to cut down on time wastage and fully utilize resources. The literature stresses on use of machine learning and parameter tuning for improved prediction in organizations that exchange data with other entities in a supply chain. In the same way, machine learning has gained an unprecedented level of accuracy necessary for forecasting the consumption of electrical devices and the overall peak demand in energy and utilities sector hence enhancing the sector's performances (Haq *et al*., 2020).

In another study (Kmiecik and Wierzbicka, 2024), the transportation and logistics sectors have enhanced the identification of the best routes with the help of machine learning and the general increase in efficiency, although the application of machine learning requires the presence of a limited amount of data and emphasizes the importance of predicting short-term demand. In a study by Ibrahim *et al*. (2020), machine learning improves water quality and resource control in water management and the environmental sectors. The study uses a method based on a Regression Tree (RT) and Self-Organizing Maps (SOM) for short-term water demand forecasting has been found effective because of unsupervised clustering over and above other models that use only one method.

Further, in (Wang *et al*., 2019; Wu *et al*., 2024) the retail and hospitality industry has undergone data-driven transformations in customer segmentation, inventory management, and recommendation systems. Research highlights the importance of predicting customer demand for effective retail supply chain management and introduces novel machine learning methods to analyze store data, including location, month, and regional factors.

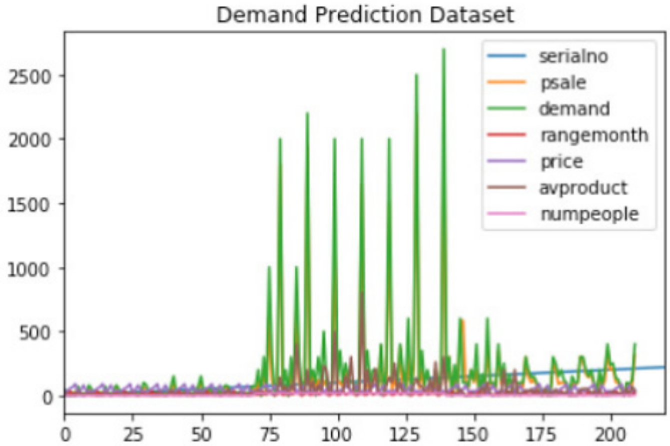

Figure 1: *Demand prediction dataset (Arif et al., 2019).*

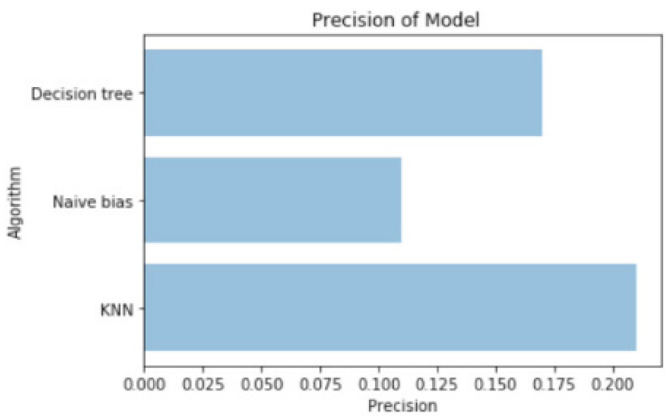

Figure 2: *Precision of model (Arif et al., 2019).*

In the pharmaceutical and healthcare sectors, machine learning has propelled advancements in drug discovery, disease diagnosis, and personalized medicine, with significant applications in demand forecasting within the pharmaceutical supply chain (Yadav *et al*., 2024).

In technology and innovation domains, advancements like autonomous vehicles and computer vision are driven by machine learning, exemplified through improved heat demand forecasting in district heating systems. These applications continue to shape industries and offer transformative potential. However, challenges related to data privacy, ethical considerations, and model interpretability persist. This review will delve into these challenges and the strategies employed to address them.

Furthermore, it will explore future directions and emerging trends in each sector, paving the way for a deeper understanding of how machine learning will continue to reshape industries and society at large. In essence, this comprehensive review aims to serve as a valuable resource for researchers, practitioners, policymakers, and businesses by providing insights into the current landscape and the potential of machine learning across a diverse range of industries. This paper highlights both the opportunities and challenges that lie ahead, with a focus on addressing gaps in existing literature and defining clear research objectives.

Related work

Machine learning techniques have become indispensable across diverse industries, enhancing operations and fostering innovation. Whether optimizing pricing in accommodation and tourism, streamlining manufacturing and supply chains, or improving energy efficiency and grid reliability, machine learning delivers tailored solutions. It also revolutionizes transportation and logistics, supports resource conservation in water management and the environment, and personalizes customer experiences in retail and hospitality. In healthcare, machine learning accelerates drug discovery and enables precise diagnosis and treatment. Meanwhile, the technology and innovation sector push boundaries with machine learning-driven advancements. This review delves into specific use cases, challenges, and future prospects in each sector. A comprehensive review of machine learning applications in diverse domains is presented in the following section.

Accommodation and tourism

Min Zhu's study (Zhu *et al.*, 2020) develops a multi-horizon accommodation demand forecast model for New Zealand, combining short-term regression and long-term time series approaches. Data from diverse accommodations assess its accuracy, outperforming naive, Holt-Winters, and ARIMA methods. In a separate work (Xie *et al.*, 2021), the authors proposed the least squares support vector regression model with gravitational search algorithm for optimizing Chinese boat excursions forecasting. This method employed big data for empirical comparisons, establishing its superiority and underlining the significance of informed forecasting. The study also examined disruptive technologies impact on supply chain management. While highlighting machine learning techniques' applications, the study lacked empirical validation.

The utilization of social media big data and machine learning for predicting tourist demand is explored in (Zhang *et al.*, 2021). Although the study showcases a valuable analytical approach to forecasting tourism demand, enhancing accuracy through broader data sources like Facebook and established tourism platforms could refine predictions further. Zhang *et al.* (2020) employed co-citation analysis, cooperation networks, and emerging trends analysis to boost global travel demand data maps. It identifies essential fields, trending research subjects, influential economies, institutions, publications, and travelers demand forecasting researchers. Using extensive knowledge maps, the study also depicts the growing interest in big data and machine learning strategies in this field.

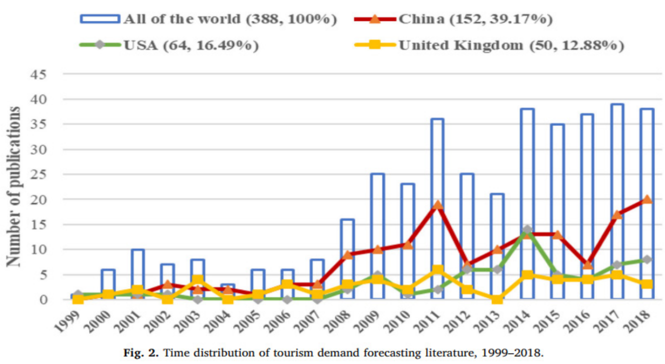

Figure 3: *The distribution of tourism demand forecasting literature, 1999-2018 (Zhang et al., 2020).*

To enhance the research's predictive precision, incorporating statistics from specific tourist spots is recommended (Law *et al.*, 2019). This study employed a deep learning approach to forecast monthly tourist arrivals in Macau. The results indicated that deep learning surpassed support vector regression and models based on artificial neural networks, effectively identifying vital features. This provides practitioners with valuable insights into factors influencing tourist arrival volumes in tourism demand forecasting.

Manufacturing and supply chain

The author in (Retail sales forecasting information systems: Comparison between traditional methods and machine learning algorithms, 2022) highlighted that numerous companies opt to share their internal data with supply chain collaborators to enhance planning efficiency and accuracy, thereby facilitating informed critical decision-making examines industrial datasets using traditional and ML forecasting methods. Parametric grid search is crucial for model effectiveness, with ML models emerging as powerful tools for industrial data analysis.

The research work (Chuang *et al*., 2021) encompasses a prominent global electronics distributor, aims to enhance prediction accuracy for procurement managers dealing with high demand volatility. To address the demand for an integrated forecasting method, a three-principle approach is followed: data pooling, theory-informed feature engineering, and ensemble-based machine learning are some of the techniques used. This methodology substantially enhances the reliability of forecasts and is commonly used. Insights gained through engagement with managers in problem context, demonstrating the value of problem-driven research strategies for advancing theoretical and methodological innovations in operations management were also shared.

Rožanec *et al*. (2021) evaluated twenty-one different forecasting algorithms using real-world data from a European original equipment manufacturer in the global automotive industry. Global machine learning models performed better than local models. Aggregating product data based on past demand helped improve forecast accuracy for global models. The research also introduced a set of metrics to assess demand forecasting model performance comprehensively.

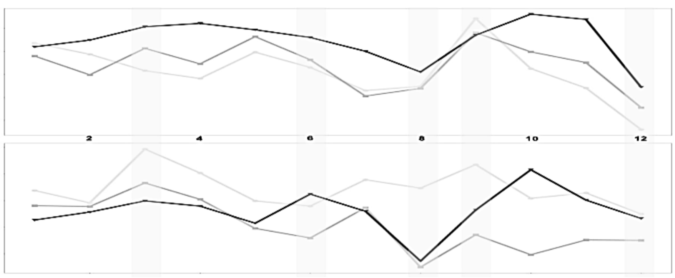

Figure 4: *Monthly demand for particular items across time Rožanec et al. (2021).*

The interaction between a buyer of customized manufacturing equipment and equipment providers in terms of demand forecasts and delivery performance was explored in (Terwiesch *et al*., 2005). Through data collection in the semiconductor equipment supply chain, the study examined how the buyer's forecast behavior (frequency and magnitude of revisions and unfulfilled forecasts) impacted the supplier's ability to meet delivery dates. The findings revealed that unreliable forecasts from buyers led to lower service levels from suppliers, and conversely, buyers provided inflated forecasts to suppliers with a history of poor service. Román-Portabales *et al*. (2021) conducted a research study focusing on demand forecasting in B2B sectors. They integrated external data sources like web crawling and Google Trends into time series and machine learning models. The results showed improved accuracy, emphasizing the value of external data for B2B demand forecasting. However, the use of external data raises ethical concerns and challenges.

In a comprehensive study, (Rožanec *et al*., 2022) presented analysis of machine learning models for demand forecasting. The study tackles irregular demand patterns through a two-phase approach, encompassing demand occurrence prediction and magnitude estimation. The article underscores tailored models and metrics for optimization and addresses underperformance concerns across different problem domains.

The findings of a massive modelling study involving automotive component demand estimation and managing inventories for a Brazilian automobile manufacturer were presented in (Rego and Mesquita, 2015). The study covers over 10,000 SKUs and six years of demand data. It explores various demand recording methods, forecasting models, and demand distribution models, resulting in 17 different policies. These policies were evaluated under (s, nQ) inventory control, with two revision frequencies and four Target-Fill-Rates (TFR). In total, 136 simulation runs were conducted for each SKU, and parameter values (s, Q) were determined to achieve the desired TFR based on established literature methods.

In another research, (Li *et al*., 2021) proposes a cost-saving algorithm for hospital blood bank inventory management. Focused on red blood cells (RBCs), this study employs machine learning, statistical modelling, and inventory optimization techniques. It examines vital scientific and operational parameters affecting daily RBC usage, delivering a flexible solution for both supply and demand issues. The study's limitations, including assumptions about storage and the application strategy, are acknowledged.

In a predictive analytics pipeline, machine learning and conventional time-series techniques may be used to address the problems in commercial aviation spare parts supply chains, as detailed in (Dodin *et al.*, 2021). This unified approach improves aftermarket demand forecasting accuracy and can be applied to diverse industries. While acknowledging some limitations, the research advances aftermarket demand forecasting, potentially enhancing supply chain efficiency across sectors. As stated by (Rožanec *et al.*, 2021), accurate demand forecasting is stressed as crucial for operational and strategic decisions in manufacturing. Global machine learning models are found to outperform local models, with data pooling based on past demand magnitude helping constrain forecast errors. The study also introduces metrics for evaluating demand forecasting models.

In a distinct research, Aamer *et al.* (2020) discussed machine learning applications for demand forecasting and performance evaluations of the techniques. A thorough investigation on the use of machine learning applications for demand projections in logistics management has already been done. Various techniques like neural networks and decision trees across industries were explained. Despite summarizing technique pros and cons, the study lacked specific performance evaluations, leaving technique selection uncertain.

Energy and utilities

A combination of metaheuristic optimization and Extreme Learning Machines to improve predicting accuracy while reducing overfitting in three forecasting models: Harris Hawk, Flower Pollination and Jellyfish Search were introduced in (Boriratrit *et al.*, 2022). The study compares the efficacy of these models to cutting-edge forecasting methods using electrical energy demand data from Thailand for the years 2018 to 2020. Based on the results, JS-ELM is the most efficient choice in this experiment given that it generates the minimal root mean square error of any of the models and maintains an appropriate processing time.

By integrating GRU and CNN, an innovative energy model for forecasting was employed by (Sajjad *et al.*, 2020) for improving prediction accuracy. It comprises data refinement and training phases, with CNN extracting features and GRU demonstrating strong sequence learning. The model is computationally efficient and precise, outperforming prior hybrid models.

A stochastic planning framework was employed by (Taheri *et al.*, 2020) for energy hubs (EHs) to address uncertainties in operational and planning studies. The framework uses a relative-likelihood impact measure to assess the importance of uncertainty sources, simplifying complex stochastic problems. Three case studies demonstrate the framework's insights into the impact of various uncertainty sources in EH planning. An article by (Mazaheri *et al.*, 2020) presents ensemble machine learning models for short-term electricity demand forecasting in industrial and residential sectors. These models enhance energy efficiency and resource allocation, utilizing computational intelligence techniques and three key data preprocessing steps.

Haq *et al.* (2020) research, smart meter data is used to forecast electrical appliance usage and peak demand with 99.2% accuracy (Haq *et al.*, 2020). Machine learning techniques, including clustering and classification, are employed to predict energy consumption patterns. The proposed hybrid method combines clustering, support vector machines, and neural networks, achieving 99.2% accuracy and benefiting power system planning and automation development.

In contrast, Gottwalt *et al.* (2011) examine the effects of smart technologies and variable pricing on household energy costs. The simulation model offers load profiles for a set price and predicts variations generated by smart appliances and time-based charges. The work presents a simulation-based method for illustrating load shifting under time-of-use regimes utilizing previously acquired profile data. This approach enables to track and handle loads in domestic power systems.

In another research by Sharma *et al.* (2021), examines the growing demand for natural gas, categorizing it into transmission-connected and distribution-connected segments. It emphasizes natural gas's significance in energy supply, exploring algorithms, software utilization by traders, and its impact on energy supply chains. The study offers a concise overview of natural gas, its historical development, industrial relevance, and forecasting methods. Additionally, it briefly covers software management, refining processes, and IT platforms in the natural gas value chain. The paper by Román-Portabales *et al.* (2021) reviewed how Artificial Neural Networks forecast electricity demand, offering insights into effective strategies and areas for improvement amid the wealth of smart meter and sensor data. In another research, the significance of power consumption prediction and the use of ANN methods was reviewed by Tsao *et al.* (2022). While lacking specific algorithm details and conclusions, it effectively outlines the review's goals, scope, and implications for future research. It focuses on the relationship between machine learning advancements and the electric grid's complexity, catering to researchers seeking insights into tailored algorithm setups for various contexts.

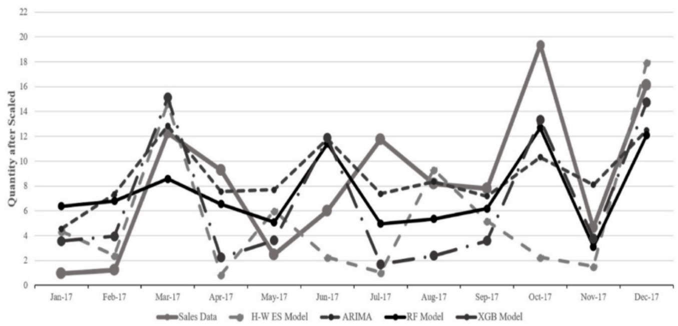

Figure 5: *Internal forecast results after scaling Tsao et al. (2022).*

A case study by Al-Musaylh *et al.* (2021) explores machine learning for energy demand forecasting, specifically for gas consumption, utilizing the EWT method. The study introduces a novel EWT-based machine learning model, involving data preprocessing, feature extraction, and model training, and demonstrates its comparative effectiveness against traditional models. While promising, issues related to integration and cost require further research to fully unlock machine learning's energy consumption potential. del Real *et al.* (2020), deep learning for energy demand forecasting, demonstrated an integrated model that merges artificial and convolutional neural networks to leverage their respective strengths was explored. The model, trained on real French energy demand data using ARPEGE weather forecasts, surpasses the performance of the subscription-based Réseau de Transport d'Electricité (RTE) service. It also outperforms alternatives like ARIMA and traditional ANN models, demonstrating the potential for highly accurate forecasting using open-source deep learning techniques.

According to Luiz-Diniz *et al.* (2018), the Brazilian power system utilizes the DECOMP stochastic programming model for weekly hydrothermal dispatch and spot pricing. DECOMP encompasses various system aspects, including interconnected areas, power demand, water inflow scenarios, and thermal plant dispatch. This paper delves into the model's mathematical details, dual dynamic programming solving strategy, and its effectiveness in representing nonlinear aspects. For an in-depth examination of the entire Brazilian system, (Sheikh and Coulibaly, 2024) contains dispatch results, merging observations, and CPU efficacy. Investigations are conducted on an authentic dataset from a Pakistani electrical supply organization to detect Non-Technical Loss (NTL). Fifteen machine learning classifiers, including CatBoost, LGBoost, and XGBoost, are evaluated. The most effective strategies for NTL detection are combined approaches and Artificial Neural Networks (ANN). Out of 71 variables, the study also finds the most significant 14 features that make up for 77% of NTL prediction.

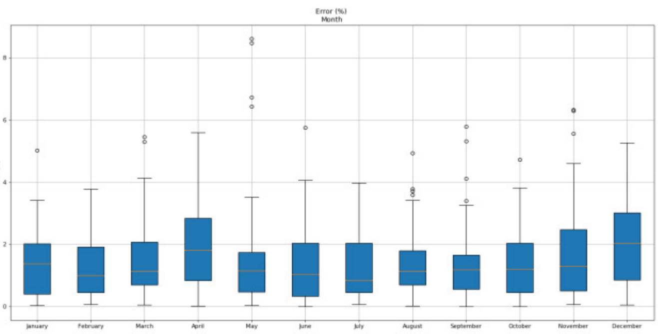

Figure 6: *Monthly absolute percentage error metrics for a whole year del Real et al. (2020).*

Saeed *et al.* (2021), the author explored load forecasting in cluster microgrids which is an under-discussed concept. For predicting short-term load demand, a number of machine learning techniques are investigated, including long short-term memory, support vector algorithms, regression analysis, and artificially generated neural networks (ANN). On a basis of performance metrics, ANN is shown to be the approach with the greatest efficacy. Additionally, three optimization techniques (Levenberg–Marquardt, Bayesian Regularization, Scaled Conjugate Gradient) are applied to enhance ANN training algorithm effectiveness.

A hybrid energy forecasting model utilizing machine learning techniques was introduced by Khan *et al.* (2020). The model includes extreme gradient boosting, categorical boosting, and random forest algorithms. Unlike conventional approaches that primarily finetune hyperparameters, our hybrid model emphasizes preprocessing through feature engineering to enhance forecasting accuracy. Additionally, we address the challenge of imputing significant data gaps and assess their impact on predictions. The model's accuracy, evaluated with a regression score (R-squared of 0.9212), surpasses existing models.

Transportation and logistics

A research undertook by Hess *et al.* (2021) focuses on short-term demand forecasting for meal delivery platforms like Uber Eats, useful for predictive routing applications in urban settings. They combine classical forecasting and machine learning methods, adapting to intermittent double-seasonal demand patterns. Empirical results reveal that an exponential smoothing method performs best when trained with at least two months of data, while machine learning outperforms classical methods with limited demand history.

Liu *et al.* (2020), an approach for predicting demand for actual on-line cab ordering was presented. It includes six models that integrate numerous sources with back propagation neural networks (BPNN) and extreme gradient boost (XGB). Results show that better prediction is possible with additional data and show demand trends for both taxis and online taxi-hailing. Resource scheduling is aided by the method's real-time online taxi-hailing forecast.

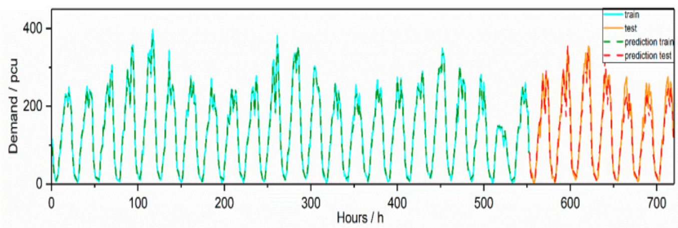

Figure 7: *Web-based demand Forecasting for cabs employing "BPNN+T+E+PTX" model (Liu et al., 2020).*

Al-Hajj Hassan *et al.* (2020) provided a method for predicting goods demand using a reinforcement learning framework that integrates time series models and machine learning algorithms. The method minimizes prediction errors, closely aligns with market trends, and reduces the need for user intervention, as demonstrated in a case study on container shipment data. It also proposes a mechanism for transforming monthly estimates into more precise the long-term weekly forecasts that outperforms conventional statistical approaches.

Water management and environment

A neural network-based technique for one-year ahead mid-term load forecasting with adjustable structure and hyperparameters was presented in (Yan *et al.*, 2022). Real-world data spanning a decade from a specific Iranian region is employed. This research looks at how economic, meteorological, and societal factors affect predicting accuracy. An effective method is proposed for bad data detection. Furthermore, the model predicts not only load peaks but also the 24-hour load pattern, aiding in mid-term planning. Simulations demonstrate the approach's practicality, achieving over 95% accuracy even in the presence of significant weather fluctuations. A four-year field study conducted by (Kukal *et al.*, 2005) aimed to find the best way to irrigate rice by using soil matric potential. By testing different soil moisture levels (80 to 240 cm), they discovered that rice yield was unaffected up to 160 cm, showing potential for efficient irrigation practices.

The study by Bata *et al.* (2020) combines Regression Tree (RT) and self-organizing maps (SOM) for short-term water demand forecasting, surpassing independent RT and SARIMA models. The incorporation of the unsupervised SOM clustering model greatly enhances the accuracy of the supervised RT forecasting model, with the hybrid models tripling the accuracy of water demand forecasting on average. The findings outperform standalone RT and SARIMA models in terms of the mean absolute percentage error (MAPE) and normalized root-mean-squared error (NRMSE) over forecasting horizons.

The case study Zhang *et al.* (2022) focuses on forecasting short-term bath water consumption in shared shower buildings at Capital Normal University in Beijing focuses. Various time series forecasting models, including autoregressive integrated moving average, random forests, long short-term memory, and neural basis expansion analysis, were employed and improved by incorporating covariates like weather, student behavior, and calendars. The models provided very accurate projections for all shower room segments, when evaluated by multiple performance indices.

To evaluate climate policies, understanding human-caused global warming under "Business-As-Usual" (BAU) is crucial (Connolly *et al.*, 2020). This study provides empirically derived estimates for future warming up to 2100, enabling comparisons with model projections. If greenhouse gas sensitivity implies a TCR of ≥ 2.5 °C, then 2.0 °C target may be exceeded by mid-century under BAU. The impact of comparisons on water demand predictions was given by (Ibrahim *et al.*, 2020). The methodologies of support vector regression linear regression and auto-regressive integrated moving average (ARIMA) are used in the study. The research was carried out employing daily water use data analysis from Kuwait. The findings indicated that ARIMA had a MAPE of 1.8 and an RMSE of 9.4, whereas Support Vector Linear Regression had a MAPE of 0.52 and an RMSE of 2.59. These findings indicated a discrepancy between the anticipated water demand and actual use, with Support Vector Linear Regression offering more precise forecasts.

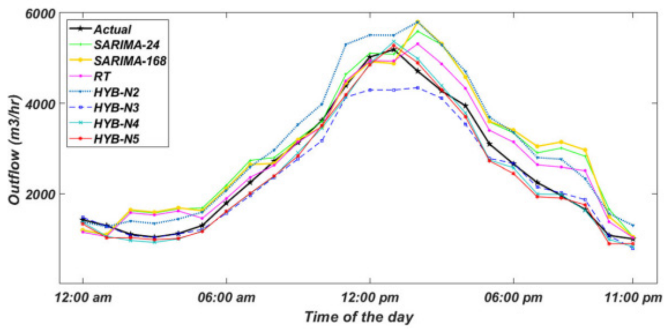

Figure 8: *Models forecasting water outflow 8 h ahead on weekend in Nov. 2017 (Bata et al., 2020).*

Retail and hospitality

According to a study conducted by (Spiliotis *et al.*, 2020), accurate forecasts are crucial for inventory management, with statistical methods like Croston's and Machine Learning (ML) emerging as alternatives. Using actual daily SKU demand data, this article contrasts machine learning and statistical approaches. The findings indicate that some ML approaches enhance accuracy and bias, particularly when cross-learning across several SKUs. A classical forecasting model with modern technologies for perishable and non-perishable items were compared in (Wang *et al.*, 2019). It assesses their performance using historical data from a large grocery retailer, considering predictive accuracy, generalization, runtime, cost, and convenience to help companies choose the best model.

Numerous techniques were evaluated in (Abolghasemi *et al.*, 2020), including statistics, machine learning, and deep learning. The shortcomings of traditional measurements are addressed by a unique statistic called Stock-keeping-oriented Prediction Error Costs (SPEC). With SPEC in consideration, the Croston algorithm outperforms others, narrowly surpassing a Long Short-Term Memory Neural Network in our findings.

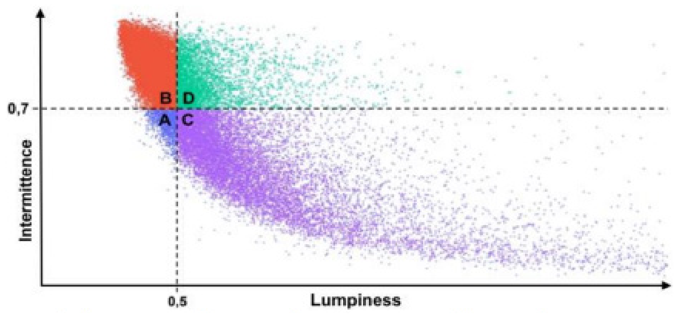

Figure 9: *Intermittence and lumpiness classification (Abolghasemi et al., 2020).*

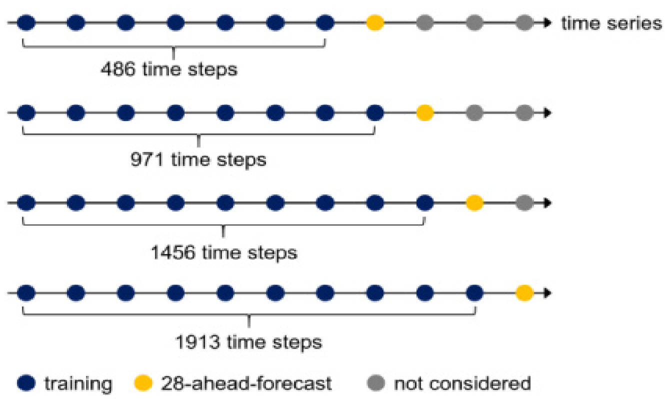

Figure 10: *Forecasting on rolling window (Abolghasemi et al., 2020).*

Similarly, in another study, Arif *et al.* (2019) introduced a novel machine learning technique for precise demand prediction in retail stores. It forecasts product demand using a variety of models such as Holt-Winters, KNN, FNN, ANN and Random Forest. The researcher employs the K Nearest Neighbor, Gaussian Naive Bayes, and Decision Tree Classifier methods while considering multiple demand-influencing elements. This approach delivers encouraging outcomes in the local market, and it suggests that the dataset be broadened with data from more urban areas and suitable techniques to be employed for more precise shop-specific demand estimates. The authors in (Abolghasemi *et al.*, 2020) discussed a unique paradigm shifting strategy for assessing periodic information and integrating it into the fundamental analytical framework. The suggested model emphasized on less systematic instances, such as unexpected environmental shifts or dynamic trading behaviors, thereby minimizing the need for frequent prediction modifications. The model is validated by comparing it to traditional statistics and machine learning models using data from two Australian firms. The results reveal improved forecast accuracy and the model's ability to overcome industry procedures that depend mainly on intuition regarding several information and occurrences. Tanizaki *et al*. (2019) presents a restaurant demand forecasting model using machine learning, emphasizing the need for store-specific models considering factors like location, weather, and events. The study discusses the construction of a model integrating these variables and validates its effectiveness with real store data.

Khan *et al*. (2020) employed monthly South Korean automobile sales and firm-level statistics from 2011 through 2020. The RReliefF method discovered important input characteristics using multiple approaches such as linear regression, neural networks, random forest, stochastic gradient descent, and ensemble learning. By integrating an ML-assisted hybrid input model and identifying previously understudied endogenous drivers, the findings advance car demand forecasting approaches and provide useful insights for improving real-world company operations.

Pharmaceutical and healthcare

The significance of blockchain and machine learning in managing COVID-19 vaccine supply chains, with a structured presentation is highlighted in (Meghla *et al*., 2021). The study emphasizes on importance of demand forecasting for vaccine allocation but lacks specific integration details and empirical evidence. Given the limited research on machine learning (ML) in the pharmaceutical industry, the study by (Yani and Aamer, 2022) explores the effectiveness of ML algorithms in demand forecasting. It identifies suitable ML algorithms and evaluates their accuracy in pharmaceutical supply chain forecasting. The research employed a single-case explanatory method, conducting experiments on training data, ML algorithms, and exclusion factors, utilizing the Konstanz Information Miner platform.

According to a research by (Zhu *et al*., 2021), In the healthcare industry's supply chain, precise demand forecasting is essential. However, issues develop as a result of insufficient data and changing market dynamics. To solve this, a unique methodology was presented that uses cross-series training and sophisticated machine learning models to harness insights from heterogeneous product data. This method also includes non-demand elements like as inventory data and supply chain information, resulting in greater performance. Empirical evidence supports the need of downstream inventory data confirmed by fieldwork.

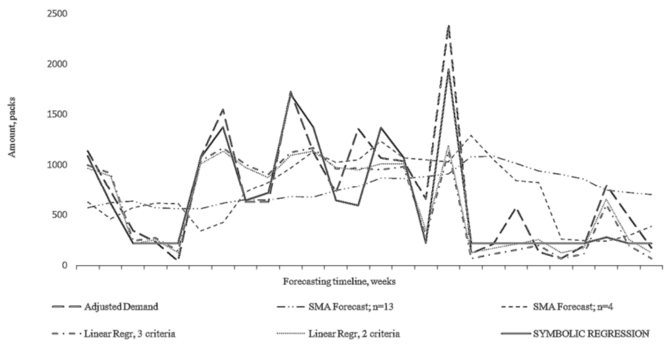

Figure 11: *Historical demand data and experimental demand forecasts (Yani and Aamer, 2022).*

Technology and innovation

In a research by (Huang and Chen, 2020), increasing need for mobile traffic and system complexity, network operators sought machine learning-based solutions were explored. The study presents an energy-aware mobile traffic offloading strategy inside a heterogeneous network, combining Deep-Q-Network decision-making with improved traffic demand forecasting. The base station control model has been developed and validated employing a readily accessible dataset from an established telecom operator. Performance studies have shown that DQN when combined with traffic forecasting outperformed other approaches across an array of mobile traffic requirements, stressing the critical nature of accurate traffic prediction, particularly under high volumes of traffic.

An innovative method that brings together the features of physics-based simulation and machine learning in particular while dealing with its restrictions is suggested in (Kannari *et al*., 2021). It employs an Artificial Neural Network (ANN) that has been taught the underlying physics using a variety of building characteristics and data from a large number of simulated structures. The accurate nature of physics-based modelling is paired with the speed, effectiveness of deployment, and refining capabilities of ANNs in this approach. Data from a range of building types were used to evaluate the ANN model's performance, which showed how well it replaced simulators. Aler *et al*. (2019), investigated the impact of incorporating real-time solar power measurements on prediction interval quality. The research explores the value of additional information for reducing uncertainty in prediction intervals. Utilizing multi-objective particle swarm optimization, neural networks were trained to predict interval bounds with inputs including measured solar power and hourly meteorological forecasts. Statistical analysis using the Wilcoxon test confirmed that measured power significantly reduces uncertainty, particularly in short-term forecasts.

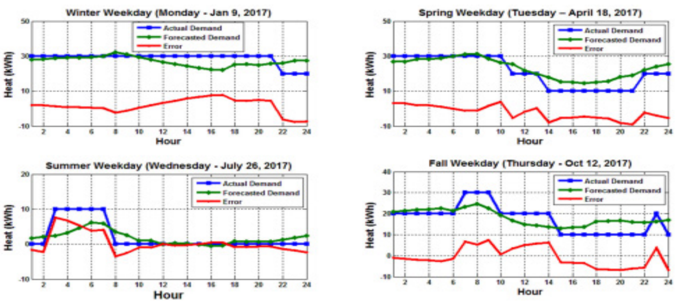

Figure 12: *Actual vs. forecasted district heat demand over the week (Eseye and Lehtonen, 2020).*

The challenge of distinguishing malicious from benign applications among naïve users are presented in (Moldovan and Riurean, 2022). It underscores the importance of designing computer systems and mobile apps to detect and protect against malicious activities. The study focuses on Artificial Intelligence (AI) techniques for malware detection, offering a comprehensive review of current technologies, their limitations, and opportunities for improvement. Embracing futuristic approaches in malware detection promises substantial advantages, serving as a valuable resource for researchers in the field. In another research, an innovative integrated machine learning approach for 24-hour ahead heat demand forecasting in a district heating system was introduced by (Eseye and Lehtonen, 2020). Empirical mode decomposition (EMD), imperialistic competitive algorithm (ICA), and support vector machine (SVM) are all used in the model. To find critical input variables, it also applies a feature selection approach based on the binary genetic algorithm and Gaussian process regression. The model is based on a two-year dataset collected from buildings in Otaniemi, Espoo, Finland.

The analysis of the literature concerning the use of the machine learning techniques in demand forecasting exposes several directions in the choice of the methodology and its implications in terms of limitations which may affect the results and conclusions. Indeed, most contributions, including Min Zhu and Chinese boat excursions have not been subjected to rigorous empirical verification thereby making the validity and applicability of their conceptual models questionable. One should note that ML heavily depends on the data quality and accessibility; thus, research that does not address the issues with data gaps, noises, or biases may provide results that are not very stable or producible in a real-word environment.

Further, since solutions like the Artificial Neural Networks (ANN) are generally more complex, there may be overfitting problems that optimize the results to a point that it cannot be practically applied in real life. Integration of information from different sources creates an issue of privacy and consent of the information, which some of the works fail to consider, this may impede adoption and use. This means that the generalizability of findings can therefore be highly dependent on the sector where the forecasting methods were developed and tested; energy forecasting tools may not easily be transferred to the retail or health care sector for instance because the systems operate in vastly different ways.

Additionally, although improved forecast complexity increases the forecast accuracy of the models, it also obstructs transparency of how those decisions are made and thus reduces trust as well as utilization of those models in the areas where their decisions will have the most impact. Most research works also have this disadvantage of not considering temporal and spatial differences that may exist in demand patterns that may lead to differences in the results gotten when compared under different geographical areas or time periods. In the same manner, it restricts the discovery to specific approaches in machine learning, which might fail to note enhancements to more effective methods in the field. To rectify these limitations and gaps in future studies, one should improve the reliability and generalization of the methods based on machine learning for demand forecasts in different industries.

Materials and Methods

Papers were reviewed on the basis of their relevance to the application areas including accommodation and tourism, manufacturing and supply chain, energy and utility, transportation and logistics, water and environment, retail and hospitality, pharma and healthcare, and technology and innovation. The assessment of the techniques was done depending on theoretical and real characteristics infrastructures including precision, speed, extensibility and constraints in applying these techniques.

Critical evaluation of forecasting techniques

In accommodation and tourism forecasting methods are; multi-horizon demand model is for New Zealand: this model integrates simple regression for the short-term forecasts and time series for the long-term projections. While this model is superior to naive, Holt-Winters, and ARIMA models, the model should be validated in other regions. The proposed method is the Least Squares Support Vector Regression model with Gravitational Search Algorithm, the growing importance of big data, but a weakness with data integration and real time usage. Applying data collected on SNA appears to present possibilities for increasing accuracy, but more general data is required. Significantly, deep learning methods perform better than its traditional counterparts, but requires more tests in different tourist areas.

When it comes to manufacturing and the underlying supply chains, the general benefits of having improved integrated planning that flows from the sharing of internal data across the network and organizations come with privacy and security costs. Spatial based machine learning improves the accuracy of the forecasting models but at the same time requires a lot of computing power. An analysis of twenty-one published algorithms proves the effectiveness of global models over local ones and stresses the importance of developing sector-specific solutions. The information exchange between buyers and suppliers discusses about the usefulness of forecast reliability concerning service levels, though the information certainly does not represent a vast OR context. The inclusion of external data improves the reliability of forecasts and, at the same time, generates questions about ethics. Responding to irregular consumer demands by exceptional models provides the best solution but that has not obtained much study on underperformance in various cases. Research on car and light truck components' demand and a hospital's blood bank need has been conducted but they need more extensive validation. Extreme learning machines, especially when incorporated with metaheuristic optimization, are more accurate but face the problem of overfitting.

Combining of the GRU and CNN enhancing the speed and efficiency of computations but require testing on different energy data sets. A stochastic planning framework reduces the problem's complexity, but its usage needs to be demonstrated in various cases. To increase the predictive capacity of short-term electricity demand, ensemble machine learning models should be used, but data preprocessing is required. The splitting of procedures results in the receipt of incredibly accurate numbers but at a cost of the necessity of enormous amounts of computational time. The use of smart technologies and variable pricing is useful in understanding consumers' behavior but unsuitable for rigorous testing of the theory in different households. Studying the forecast of natural gas demand focuses on its significance while calling for more investigation of applying machine learning in IT systems. The paper on ANN methods presents ideas that can be helpful but requires more specific information on algorithms and recommendations.

In transportation and logistics, the short-term demand forecasting for meal delivery platforms is done with both, the classical and the machine learning approach but due to the intermittent double-seasonal demand it is not without further challenges. However, while forecasting the demand for ordering cab online, the need is pointed to use a variety of sources which, however, it is more accurate in the conditions of real-time data. It is noteworthy that the given Reinforcement Learning framework consists of techniques that minimize the prediction differences; still, there is a need to perform the experiment in various transportation contexts. One of the load forecasting techniques is the one that incorporates a model known as the neural network and research carried out have revealed that this method is accurate but the accuracy has to be experimented in other regions. Thus, the proposed method utilizing aspects of the Regression Tree and self-organizing maps increases accuracy, but more work needs to be done to examine its applicability to different water demand conditions. The results of the bath water consumption suggest that there is potential for very precise predictions, but the procedure should be fully validated in many terminals. Information comparing climate policies and other approaches of prediction provides relevant information, yet it requires more focus on the interconnections of the methods.

Thus, in retail and hospitality, inventory management forecasting brings together cross-learning concerning various SKUs with overall generalization issues. Comparing classical and modern forecasting models provides useful information but needs check in other spheres of retailing. The performance comparison of different methods demonstrate that the Croston algorithm yields the best results, though a larger scope of implementation is required. A new methodology in the use of the MDP for demand prediction yields good results, but needs a rigorous crosscheck in different environments. This study demonstrates that periodic information enhances the accuracy of analytical frameworks in forecasting but more studies need to be done on the use of periodic information in the different industries. Restaurant demand forecasting models reveal the necessity of having store-specific models; however, they should be validated using various datasets. Since blockchain and machine learning are already in use in centralizing COVID-19 vaccine supply chain networks, though the work focuses on clarifying the demand forecasting importance, it overlooked certain minutiae about the integration procedures.

Discussing the application of ML algorithms within the pharmaceutical supply chain suitable algorithms are found but require a study of their empiric efficacy. A method for using explorative insight for non-homogeneous product data is presented with enhanced execution but insufficient evidence on non-demand factors incorporation.

In facets of technology and innovation, mobile traffic solutions based on machine learning stress on the accuracy of traffic forecasting but are confronted with issues of Increased volumes of traffic. Using combined physics-based simulation with machine learning shows a high potential, however, it should be tested with different types of buildings. There is benefit in having additional information derived from real-time measurement of solar power but it needs to be expanded on further. Discriminating between the applications with an ill-intent and those that are benign stresses the use of intelligence in the malware detection but calls for further studies on how to combine various approaches that have been discussed. An approach for the forecasting of the heat demand is being presented here which has a number of advantages but which needs further substantial verification in various environments.

Comparative analysis of forecasting techniques

The comparison of these forecasting techniques shows that most of the machine learning models have a higher level of accuracy and flexibility as compared to the conventional model. Deep learning models outperform support vector regression and artificial neural networks in the accommodation and tourism industry. Application of ensemble-based machine learning leads to improvements in the reliability of the forecasts that are very valuable in manufacturing and supply chain management. In the energy and utilities classification, high accuracy is maintained but at the cost of high computational complexity. It was possible to achieve a high degree of hybridization between classical and machine learning methods for decision-making in the transportation and logistics sector, but there are issues with transitioning to unpredictable DS2 demand fluctuations.

The cases of hybrid models in water management and the environment greatly improve accuracy but need to be more often used and applied in different situations. Improvement for the training across SKUs in the retail and hospitality sectors of accuracy is seen, though addressing generalization issues. There is evidence of improved supply chain performance when non-demand elements in the pharmaceutical and healthcare sector are included, but to some extent, the literature lacks preliminary research on the holistic integration process. Uncertainty and unpredictability are inevitable in technology thus the importance of predicting traffic accurately under conditions of high traffic as offered by innovation.

It reveals that there is a need to develop industry-specific forecasting models, which postulate and test apparent industry issues. For future research, the utilization of knowledge for improving aspects of data integration for various and real-time data sources should be considered as well as the further investigation of the ethical concerns in a machine learning environment, mainly comprising data privacy and security as well, future studies must be more extensive in terms of validation studies across various geographic and industrial regions required for checking generalizability across different geographic and industries Must modernized scaled techniques that can be easily adapted depending on.

Practical implications of forecasting models

The practical implications of the reviewed studies also stress on the conclusion that each industry might encounter different issues and, thus, requires a particular forecasting model. Ensemble based methods have been used in manufacturing and supply chain to enhance reliability of the system but arrives at higher computational costs. Subsequent investigations should be directed toward refining the mechanisms of information merging procedures for various, up-to-date sources, and specific ethical issues related to data protection should be more closely examined.

Future research work should apply the solution in different geographic and industrial domains to determine its applicability and stability, also, more experiments with the hybrid models must be conducted in water management and the environment domain as promising in terms of accuracy, but require further validation. The need to create suitable methods that can effectively address the different data size and characteristics is also quite important while trying to seek how to blend the traditional and the new machine learning methodologies.

The actual schedule use of the forecasting models is critical for the functioning of several industries, such as transportation and logistics. Such areas should be given concern in subsequent researches in order to enhance the development of better and diverse accurate, flexible and ethical forecasting models that fit into various industries.

Conclusions and Recommendations

Therefore, this review has established that machine learning has been revolutionary in many industries. It has notable enhancements in customer relations, operational systems, utilization of energy, and handling of the environment. Many industries such as transportation, logistic, retail, hospitality, pharmaceutical, healthcare, and technology have significantly benefited from machine learning stochastic improvements and new solutions.

In turn, such advantages as the constant improvement of the technology and increased efficiency come at costs, including the evaluation of ethical issues and data protection. Thus, future research should be directed towards the construction of less prone, explainable models for concrete industries. It is imperative to assess unequal treatment and general methods used for making decisions and implement best practices while considering regulations and ethical issues of machine learning, especially in the areas that extremely affect people's lives like healthcare and energy. In conclusion, machine learning is expected to remain the most influential field and to become the key engine for development and the solution of various challenges and undertakings in the interconnected environment.

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Novelty Statement

This review paper offers a novel contribution by providing a comprehensive cross-industry analysis of machine learning applications, showcasing how this technology is transforming diverse sectors such as accommodation, tourism, manufacturing, healthcare, and beyond.

Author's Contribution

Syed Zeeshan Ahmed Naqvi: Responsible for research, data analysis, and drafting of the paper.
Aftab Khan: Guidance, assisted literature review, drafting, and overall structure of the paper.
Abdul Majid: Assisted in data collection and provided insights into machine learning applications.
Tahir Javed: Contributed to literature review and analysis of specific use cases in different industries.
Muhammad Huzaifa: Supported in final revisions, editing, and addressing reviewer comments.

Conflict of interest

The authors have declared no conflict of interest.

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