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RESEARCH PAPER

AI-Based Demand Forecasting Models: A Systematic Literature Review

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ABSTRACT
In today's dynamic and competitive manufacturing landscape, accurate demand forecasting is paramount for optimizing production processes, reducing inventory costs, and meeting customer demands efficiently. With the advent of Artificial Intelligence (AI), there has been a significant evolution in demand forecasting methods, enabling manufacturers to enhance the accuracy of the forecasts.
This systematic literature review aims to provide a comprehensive overview of the state-of-the-art on demand forecasting models in the manufacturing sector, whether AI-based models or hybrid methods merging both the AI technology and classical demand forecasting methods. The review begins by establishing an overview on demand forecasting methods, it then outlines the systematic methodology used for the literature search.
The review encompasses a wide range of scholarly articles published up to September 2023. A rigorous screening process is applied to select relevant studies. Accordingly, a thorough analysis in the basis of the forecasting methods adopted and data used have been carried out. By synthesizing the existing knowledge, this review contributes to the ongoing advancement of demand forecasting practices in the manufacturing sector providing researchers and practitioners an overview on the advancements on the use of AI models to improve the accuracy of demand forecasting models.

KEYWORDS: *Demand forecasting; Forecasting models; Artificial intelligence; Supply chain.*

1. Introduction

In an ever-evolving economic context, industrial companies are increasingly exposed to external shocks, including but not limited to pandemics, geopolitics, climate change, and more. The resilience of the supply chain and its ability to adapt to multiple organizational challenges are becoming crucial competitive factors for industrial enterprises. Considered as the starting point of Supply Chain Planning (SCP), Demand Forecasting plays a fundamental role in strengthening the resilience of a supply chain [1] [2].
Demand forecasting is a critical aspect of modern business operations and supply chain management. Accurate forecasts enable companies to make informed decisions regarding production, inventory management, and resource allocation.
Time series data have historically played a major role in the development of forecasting models. However, disruptions in value chains and inconstant customer preferences have raised concern about the reliability of traditional forecasting models and their limitations in accurately predicting demand behavior. The emergence of disruptive technologies, and in particular artificial intelligence, present an opportunity for enhancing the reliability of demand forecasting.
In recent years, artificial intelligence (AI) has emerged as a transformative force across various industries. AI technologies, including machine learning, deep learning, natural language processing, and computer vision, have demonstrated remarkable capabilities in data

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analysis, automation, and decision-making processes. This transformation has not gone unnoticed within the realm of demand forecasting. AI, with its ability to handle vast datasets, recognize intricate patterns, and adapt to changing conditions, offers a promising avenue for revolutionizing how organizations predict and manage demand. As businesses seek to gain a competitive edge and respond swiftly to market shifts, AI's potential to enhance the accuracy and efficiency of demand forecasting has become increasingly appealing.

Recently, the use of artificial intelligence in demand forecasting in the manufacturing industry has garnered the interest of numerous scientific researchers. This interest is evident through the growing number of scientific publications that propose forecasting models based solely on artificial intelligence, as well as those combining AI models with time series data, known as hybrid models [3].

This review aims to explore the application of AI methods in demand forecasting, shedding light on their strengths, limitations, and real-world implications. In light of the growing number of research publications in this scope, this article serves as a systematic literature review to summarize the existing knowledge on AI-based Demand Forecasting models in the manufacturing industry. For this purpose, this paper will be structured as follows: Section 2 provides an overview of the scope and background for our research. Section 3 outlines the methodology and protocol employed for conducting this Systematic Literature Review. Section 4 describes the findings and outcomes derived from the SLR, section 5 explores the findings and results drawn from the collected material, and lastly section 6 serves as the conclusion of the SLR, offering insights and the study's limitations.

2. Background

2.1. Artificial intelligence

Due to advancements in computer science and the research in 4.0 technologies, Artificial Intelligence (AI) has significantly evolved since the late 20th century. Its definition has continually changed since its inception in 1950 by mathematician Alan Turing [4]. Afterwards, the modern phase of AI began with the Dartmouth Summer Study Group on Artificial Intelligence in 1956. The increase in computing power has contributed to the rise of artificial intelligence [5].

AI is a prominent technology in the industry 4.0 field; it is defined as the creation of systems and machines capable of performing tasks that typically require human intelligence such as learning from data and making decisions and predictions, problem solving and understanding natural language. Its ultimate goal is to develop "thinking machines" that can mimic, learn, and even replace human intelligence [6].

Various definitions of AI are found in the literature that complement each other, among others, Marvin Lee Minsky (1956) characterizes AI as the development of computer programs designed to perform tasks that currently benefit from human involvement due to their reliance on advanced mental processes like perceptual learning, memory organization, and critical thinking. Meanwhile, Bringsjord and Schimanski define intelligence as excelling in all established and validated intelligence tests [7]. According to [8], AI is a cross-breeding of several methods and phenomena including Neural Networks (NN) and Deep Learning (DL).

Artificial Intelligence has been applied in many areas, namely, healthcare, finance, energy, education, manufacturing, self-driving cars and virtual assistants. Until 2021, the economic contribution of AI technologies was estimated to be around $13 trillion by 2030 [9].

On the other hand, AI had several applications in all Supply Chain field, from upstream to the downstream ones, i.e. Risk Management, warehousing, Supplier relationship management, Supplier selection, manufacturing, demand forecasting and demand planning, inventory management, transportation and distribution. The application of AI in supply chain provides a surprising result in processes optimizing, costs reduction, Supply Chain efficiency and resilience enhancement.

As for demand forecasting, AI contributed to improve forecasts accuracy and efficiency of predicting future demand for products or services through Real-time Data Analysis, Demand Sensing, Inventory optimization, Product Lifecycle Management, etc.

2.2. Demand forecasting

Demand forecasting is a proactive process of making predictions and anticipate the future demand and customer requirements, including sourcing, manufacturing, transportation, and operational tasks [10] based on historical data, market analysis, and other relevant factors. Its primary goal is to estimate how much of a particular product or service customers will want or need in the coming days, weeks, months, or even years.

Demand Forecasting serves as the initial step for production planning, procurement, inventory management, new product development, marketing campaigns, etc. Thus, it is a crucial tool for businesses to anticipate and prepare for changing market conditions, manage resources efficiently, and make informed decisions that drive growth and profitability [11].According to [5], the global value of predictive analytics application field is estimated at more than 10 billion dollars, so it constitutes the most important element for business. Also, Demand prediction is one of the most interesting research issues [12].

Among the features of forecasts discussed in the literature, we find the forecast horizon, which can be hourly, daily, weekly, monthly, and annually [13]. As well as load forecasting which can be short-term (from one hour to one week), medium (from a week to a year), and long-term forecasts (more than a year) [14].

2.3. Demand forecasting methods

Demand forecasting involves predicting the future demand for a product, which aids in organizational planning. Typically, it relies on sales forecasts and the management of demand. This prediction plays a crucial role in a company's decision-making process. Nonetheless, it is vital to possess a thorough grasp of various forecasting techniques to create accurate forecasts.

All conventional forecasting methods, including exponential smoothing, moving averages, time series analysis, and Box-Jenkins approaches, share a common trait: they assume that future demand will mirror past demand patterns. Consequently, the effectiveness of these methods relies heavily on the reliability of historical consumption data, making it challenging to predict future demand for new products or services with no historical data. Moreover, in a rapidly evolving data-driven environment, the value of forecasts in business hinges on their accuracy. Consequently, researchers have increasingly focused on this realm, blending traditional forecasting methods with artificial intelligence algorithms to enhance forecast accuracy [15].

There are several modelling techniques to elaborate demand forecasting, the choice of the appropriate ones depends of forecasting horizon, data availability, business requirement and data pattern [16]. However, there has been no universal classification of demand forecasting methods in the literature so far. The table 1 categorizes demand forecasting methods according to a number of researchers.

Tab.1. Demand forecasting methods categorization

Ref	Classification	Description	
[17]	Qualitative	Estimation based on expert judgment	
	Quantitative	Based on mathematical model and objective analysis	
[10]	Qualitative	E.g.: Executive opinions, Delphi technique, Sales force polling and Customer services. Based on opinion.	
	Quantitative	Historical data forecasts E.g. Naive method, Trend Analysis, Time Series Analysis, Holt's and Winter's models.	
[18]	Statistical methods	Rely on historical data and mathematical models to make prediction	
	AI-based forecasting methods	Use AI techniques	
[11]	Conventional	Survey methods	Collect and analyse the information from different sources to predict forecasts. E.g. Delphi's method
		Statistical methods	Based on historical data E.g. MA, Regression analysis
	Non-conventional	Includes AI tools and complex mathematical models	
[19]	Traditional statistical methods	E.g. Bayesian approach, auto-regression, exponential smoothing, Holt-Winters model, ARIMA and SARIMA.	
	AI methods	E.g. ANN, ELM, GM, FL, GM	
[20]	Linear	E.g. ARIMA, Linear Regression Model, exponential smoothing Use univariate time series analysis	
	Non-linear	E.G. ANN, SVM, GA, expert sustems Use Non-Linear Regression Model	
[13]	Causal methods	E.g. ANN, regression models Cause and effect relation	
	Data based methods	Based on historical data	
[21]	Conventional models	E.g. Time series models Regression models Gray models	
	AI-based models	E.g. ANN, SVR, RF	

Numerous papers have studied the use of different demand forecasting methods in specific areas, for example, [3] analyzed the methods used in fashion demand forecasting, concluding that the most commonly used are exponential smoothing, Regression models, Neural networks, survey-based methods.

Artificial Neural Network is the most efficient method of prediction, it is used to improve statistical methods [1][2]. Nevertheless, despite the satisfactory results of the AI methods, there are still shortcomings that need to be improved. To this end, there is an increasing tendency to use hybrid models based simultaneously on statistical and AI-based models.

2.4. Demand forecasting performance

Measuring the performance of demand forecasting is essential for evaluating the effectiveness of forecasting methods and improving the accuracy of future prediction. Forecasting performance is correlated to forecast accuracy, which is assessed by several key performance indicators.

To, assess forecasting performance, the metrics mainly used by researchers are [10]:

- **Mean Absolute Error (MAE):** This is the average of the absolute values of the differences between forecasts and actual demand. A lower MAE indicates better accuracy
- **Mean absolute range normalized error (MARNE)**: It normalizes the error by dividing MAE by the range of the actual values, making it independent of the data scale.
- **Mean Squared Error (MSE)**: Calculates the average of the squares of the differences between forecasts and actual values.
- **Root Mean Squared Error (RMSE)**: It is the square root of MSE.
- **Normalized root mean squared error (NRMSE)**: It is a normalized version of RMSE.
- **Mean Absolute Percentage Error (MAPE)**: Calculates the average of the percentages of absolute error between forecasts and actual values expressed as a percentage.
- **Accuracy Rate**: measures the proportion of correct forecasts in relation to all forecasts.
- **Bias**: Measures the overall tendency of forecasts to be either too high (positive) or too low (negative) in relation to actual values. A bias close to zero indicates a balanced forecast.

To get an overview of demand forecasting performance, it is common to use several of these metrics simultaneously. The purpose is to identify the areas where forecasts are least accurate and to make continuous improvements to forecasting methods to optimize the whole of supply chain fields.

Several factors should be taken into consideration when determining how to measure forecast errors or accuracy within each level of a supply chain. Furthermore, it is worth noting that collaborative forecasts among upstream organizations, based on end customer sales, can help reduce forecast errors.

While these performance measurements across various studies predominantly concentrate on forecasting accuracy, ref. [19] uses MSE, MAPE and MAE and conducts evaluations of the performance of several popular forecasting methods, taking into account diverse factors such as accuracy, speed, data requirements, stability, ease of use, and other relevant parameters. As for [21] , the authors used R^2, MSE, MAE, MAPE, RMSE and MARNE to assess the effectiveness of the models.

2.5. Related literature review

As a first step towards our systematic literature review, we have tried to map the existing reviews related to our scope of studies; the use of AI models in demand forecasting. We have identified a number of papers that has presented extensive reviews on demand forecasting methods within the scope of AI. Table 2 highlights some of the reviews that were close to our research.

Tab. 2. Overview of demand forecasting methods used in the literature

Ref	Year	type	Period	Number of articles	Sector	Description	Method's type	GAP
[22]	2023	SLR	2008 - 2018	64	-	This SLR compares the accuracy of machine learning models, data processing method and research variable employed in demand forecasting using machine learning.	ML	The study offers limited insight into how ML techniques are applied to solve specific industry forecasting challenges or into the assessment of data quality.
[23]	2023	SLR	2002 - 2022	50	SC	In this SLR, the authors summarize AI's applications in all sub-field of the Supply Chain.	AI methods	The review does not deal in detail with the use of AI-based forecasting methods.

Ref	Year	type	Period	Number of articles	Sector	Description	Method's type	GAP
[2]	2022	SLR	2017 - 2021	-	SC	The purpose of this SLR is to select the appropriate AI methods that improve forecast accuracy. The authors clusstred the methods in order to define their trend. Then they classified methods considering volume of data, time horizon and dimensionality of data.	AI methods	The SLR classifies AI forecasting methods according to data dimensionality, volume, and forecast horizon. However, it notably lacks an analysis concerning the nature of the data.
[24]	2022	Study	-	-	-	This study compare Statistical forecasting and AI-based models with practice-based models in SME's and large firms.	Statsitical, AI and hybrid	The study does not provide an in-depth analysis of the data used, and only focused on the prophet model.
[25]	2022	Litterature review	from 1997	47	Power demand	This litterature review summarize autoregressive methods to short-term applications in power demand forecasting.	Autoregressive	The Litterature review is limited to statistical methods in the power demand sector.
[9]	2021	SLR	1998 - 2020	150	SC	The present SLR gives an outline of studies that handle AI applications in SCM.	Statsitical, AI and hybrid	the study deals with AI applications in the supply chain and does not analyse the data used.
[26]	2021	SLR	2000 - 2020	267	Energy	The present paper is a review of papers related to forecasting methods in the industry of energy.	Traditional and intelligent methods	The study focuses on the energy sector.
[27]	2021	SLR	2010 - 2021	100	Water	This SLR reviews predictive methods considering short-term water demand, it is a guideline for engineers and practitioners on chosing a water demand forecasting method to use among the multiple available options .	statsitical, AI and hybrid	The SLR does not review the studies carried out on forecasting methods in the manufacturing sector.
[28]	2019	Literature review	1980 - 2018	1235	Emergency ressources	The authors classify and analyze current research on demand forecasting methods and applications.	Statsitical, AI and hybrid	The authors present an overview of demand foreasting methods without analyzing the data employed.
[11]	2019	Litterature review	-	-	-	This paper compares conventional methods and non-conventional models of different forecasting related parameters.	Conventional and Non-conventional techniques	The study does not provide an in-depth analysis of the data used.
[29]	2019	Litterature review	2007 - 2017	-	Tourism	This paper reviews the current literature regarding tourism demand forecasting. It shows that combined forecasting methods are offering better forecasts correlated to the traditional forecasting methods.	Statsitical, AI and hybrid methods	The review restricts its examination of forecasting methods exclusively to the tourism sector, omitting a vast analysis across different industries.
[21]	2019	SLR	1990 - 2019	116	Energy	The aim of this review is to define the purpose of forecasting, forecasting horizons, data properties, applied areas, data preprocessing methods, and forecasting methods in the papers reviewed.	Conventional and AI-based models	The SLR does not review the studies carried out on forecasting methods in other sector except Energy.
[13]	2016	Overview	2005 - 2015	-	Energy	this paper outlines traditional and soft-computing based techniques in forecasting.	Traditional techniques and soft computing methods	The review analyses forecasting methods only in Energy sector.
[30]	2012	Litterature review	2000 - 2010	-	Water	Review of methods and models useful for specific water utility decision making problems.Applications of the urban water demand forecasting	Statsitical, AI and hybrid	The review analyses forecasting methods only in Water sector.

Ref	Year	type	Period	Number of articles	Sector	Description	Method's type	GAP
						models differ, depending on the forecast variable, its periodicity and the forecast horizon.		
[20]	2019	Litterature review	-	-	Water	This review studied the models developed based on statistical techniques, among as soft computing techniques's base, linear regression and tyme-series analysis.	Linear, non linear & hybrid models	The review analyses forecasting methods only in Water sector.
[14]	2013	Overview	-	-	Energy	The present paper reviews electricity demand forecasting techniques that can be represented in three main groups: Traditional Forecasting technique, Modified Traditional Technique and Soft Computing Technique.	Traditional, Modified Traditional and Soft Computing forecasting techniques	The review analyses forecasting methods only in Energy sector.

The table highlights significant gaps in research concerning the application of AI in forecasting across various sectors. Most studies focus narrowly on specific industries like energy, water, and tourism, omitting a broader range of industries, notably manufacturing. Moreover, there is a notable lack on the analysis of data nature and quality, highlighting a crucial gap concerning data analysis. The efficacy of any AI-based forecasting model is influenced fundamentally by the quality, relevance, and completeness of the data used, underscoring the importance of thorough data evaluation in research. [2] [6]

Accordingly, we have identified a lack of reviews on demand forecasting models in the industrial and manufacturing sector in light of AI models; a critical area given its direct impact on production scheduling, inventory management, and overall supply chain. Consequently, we have chosen our research scope to explore the state of the art in AI and hybrid demand forecasting models within the industrial and supply chain sector, between 2019 and 2023 ensuring a comprehensive and coherent examination. Furthermore, we will provide a detailed analysis of the data used in these studies, examining their nature and volume.

3. Methodology

The emergence of new Information and Communication Technologies (ICT) has made sharing scientific research accessible to an ever-expanding scientific community and has facilitated the emergence of new areas of exploration [31]. The challenge now is to ensure the reliability of data presented in scientific publications while preserving the integrity of the research process. Therefore, the Systematic Literature Review (SLR) has become indispensable for scientific documentation.The aim of an SLR is to critically address the research field by conducting a cross-cutting analysis of various previous research works and objectively comparing the results [32]. To achieve this, the approach involves collecting, analyzing, and synthesizing all publications related to the said scope. the key characteristics of a rigorous literature review should be systematic, explicit, comprehensible, and reproducible [33].

It is within this context that the current work is positioned. It serves as a foundation for contemplating the endeavors in scientific production aimed at developing mathematical models or deploying artificial intelligence (AI) algorithms to enhance demand forecasting reliability in an industrial setting.

Many authors have provided guidelines to assist researchers in conducting SLRs in various fields. This work follows a methodology inspired by [33] and [34], which, in turn, adopt Mayring's methodology [35]. The execution of this systematic literature review follows the three stages mentioned by [31]: Planning, Conducting the review, and Reporting the review.

3.1. Planning

The planning step in a systematic literature review is crucial because it sets the foundation for a well-structured, unbiased, and rigorous review process. This step will highlight the following stages:

3.1.1. Current state

The primary objective of this study is to build upon previous work that has explored the applications of artificial intelligence in the Supply Chain [15]. To determine the framework of this work, a primary search was conducted to explore existing literature reviews and define the research gap. Initially, we focused on literature reviews that emphasize the use of artificial intelligence in demand forecasting within the industrial domain. This helped identify a need for comprehensive review addressing this topic.

3.1.2. Review protocol

In order to clearly define the research objectives and scope, we established a protocol that will enable us to conduct this work in a clear and precise manner. The first step is to address the key questions that govern our research:

- What are the AI-based models and algorithms used in Demand Forecasting?
- What data is utilized?

The research focused on identifying the models and algorithms used for demand forecasting within the manufacturing industries, as well as the various parameters employed in creating these models.

We conducted a literature search on the "Science Direct" and "Scopus" databases using four keywords: "demand forecasting," "artificial intelligence," "modelling," and "supply chain." In order to conduct a comprehensive search, we used connectors such as "AND" and "OR" to include various combinations of these keywords. Next, we selected papers written in English, sourced from scientific journal articles, proceedings, and book chapters, published between January 2019 and September 2023.

3.1.3. Inclusion and exclusion criteria

To better delineate the research scope, we have defined inclusion and exclusion criteria, which are summarized in Table 3.

Tab.3. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Papers within the industrial field	Papers dealing with the following sectors: Tourism, Agriculture, Weather, Energy & water consumption, health (E.g. covid 19 cases, blood demand), services sector, construction sector.
Upstream Supply chain	Retail, mobility & transportation
Demand forecasting	Sales forecasting
Articles published between 01/2019 and 09/2023	Articles published before 2019
Research papers, proceeding, book chapters	Literature reviews

3.2. Conducting the review

We conducted this review based on the methodology followed by [32] and [33], which consists of four main stages detailed as follows: Material collection, Descriptive analysis, Category selection and Material evaluation.

3.2.1. Material collection

First, we conducted our research in accordance with the aforementioned protocol, including the database searches, keywords, publication period, language, etc. Next, we made an initial selection based on the predefined inclusion and exclusion criteria. Subsequently, we conducted a second round of selection after screening the review of all the preselected papers. Finally, we removed duplicates and selected the articles that will be analyzed in the following stages.

3.2.2. Descriptive analysis

Descriptive analysis enables the extraction of general information and basic characteristics related to the article, including the author, publication year, keywords, journal name, paper type, and industry, among others. The synthesis of these characteristics and the analysis of the extracted data will provide a general overview of the distribution of the papers under study.

3.2.3. Category selection

Categorization simplifies the analysis and contributes to the objective evaluation of papers. The identification of these categories was done gradually during the in-depth reading of the selected articles. Therefore, to analyze the statistical models and algorithms used to enhance sales forecast accuracy, we have defined the following two main categories: Forecasting Methods and Data Utilized.

3.2.4. Material evaluation

This step is crucial for assessing the relevance of the adopted methodology and the conducted analysis. After collecting all the information according to the categorization, we evaluated the results obtained. The presentation of this evaluation is the subject of the discussion section.

3.3. Reporting the review

After selecting the papers for the reviewing, we proceeded with the analysis. Subsequently, the synthesis of all the work conducted has been presented in this article following the structure proposed by [31].

4. Findings

4.1. Descriptive analysis

The initial search was conducted on the "SCOPUS" and "Science Direct" databases between January 2019 and September 2023, using various combinations of the keywords "demand forecasting," "artificial intelligence," "modelling," and "supply chain." This search identified 6136 articles. Eliminating literature reviews reduced the count to 5434 articles.

Thereafter, a primary selection was made based on the examination of titles, abstracts, and keywords, resulting in a preselection of 306 articles. After removing duplicates, 286 articles remained. Finally, following a full-paper evaluation, 33 scientific publications were selected for in-depth study. Figure 1 summarizes the steps followed for the selection of articles to be reviewed.

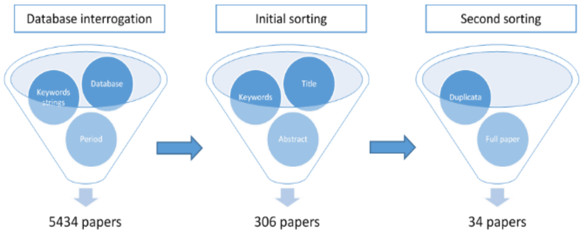

Fig. 1. Material selection process

4.1.1. Publications per year

Fig.2 depicts the evolution of publications during our selected time span. The average number of publications is around 8 articles per year from 2019 to 2022. However, in 2023, the number of articles published until September is limited to two.

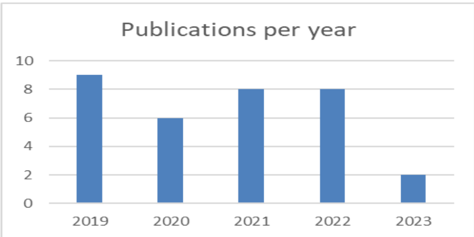

Fig. 2. Distribution of papers per year of publication

4.1.2. Publication type

The majority of the selected publications are journal articles, comprising 76% of the total, which amounts to 26 articles out of 34 in total, followed by conference proceedings and book chapters (fig. 3).

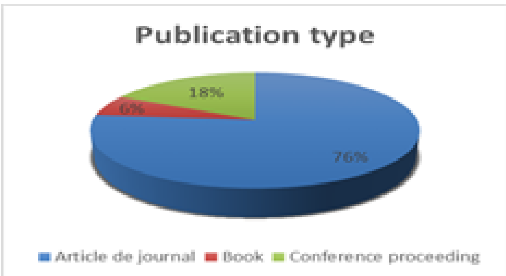

Fig. 3. Distribution of papers per Publication type

4.1.3. Industry

Among the inclusion criteria listed in the research protocol mentioned earlier, the articles included in this systematic literature review must pertain to a manufacturing sector. Therefore, the figure indicates that 18% of the models developed for demand forecasting have been applied in the pharmaceutical industry, 18% in the automotive industry, and 12% in the electronics industry (fig.4).

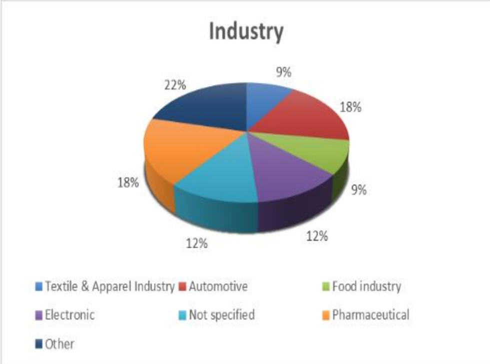

Fig. 4. Distribution of papers per Industry

4.2. Category selection

4.2.1. Forecasting methods

The present SLR aims to study forecasting methods that utilize artificial intelligence. Therefore, a thorough analysis of the selected publications was conducted to comprehensively examine the models, algorithms, and forecasting methods used. The figure illustrates the distribution of publications between those that employed a forecasting approach solely based on Artificial Intelligence and those that adopted a hybrid approach combining AI and statistical models.

On the other hand, the figure groups together the models and algorithms that have been used by more than two authors, along with their frequency of usage.

Thus, demand forecasting methods have been classified into 5 categories, namely, Statistical or AI-Based, Baseline or Statistical or Machine Learning (ML) methods, Conventional or Non-Conventional, Linear or Non-Linear, Causal or Data-Based.

Table 5 in Appendix provides information about the methods, models, and algorithms used in demand forecasting across all selected articles, along with their categorization based on the aforementioned categories.

- **Statistical methods**: Based on statistics models and rely on historical data to make prediction. They are effective for forecasting when data patterns are stable and can be modeled accurately. [36]
- **AI-Based methods**: Forecasting methods that leverage artificial intelligence techniques to make prediction, they are able to handle complex and non-linear relationship in data and to make prediction even when historical patterns are less stable.
- **Baseline methods**: Simple to implement, nevertheless, they are limited in their ability to capture complex patterns and trends present in more advanced forecasting techniques. They are employed when more sophisticated models are not available or when a simple approach is sufficient
- **Machine Learning (ML) methods**: Involve the use of advanced machine learning techniques to make predictions about future events, trends, or values. [36]
- **Conventional methods**: Conventional methods are tried-and-true techniques that have been used for many years and have a well-established theoretical foundation, their implementation and understanding are relatively simples [11].
- **Non-conventional methods**: Are innovative and more complex, they involve the use of advanced technologies such as Artificial intelligence to make forecasts [11].
- **Linear methods**: Are simple and easy to understand and assume that the relationships between variables are linear, namely they can be represented as straight lines or planes in a graph. This implies a constant rate of change between variables [20].
- **Non-linear methods**: Are more complex, as they involve higher-order equations or complex mathematical functions which allows them to capture more intricate data patterns [20].
- **Causal methods**: Involves modeling the cause-and-effect relationships between variables. It assumes that changes in one or more independent variables cause changes in the dependent variable. These methods often use statistical regression models or econometric models to quantify and analyze these relationships [13].
- **Database methods**: rely on historical data, it leverages the data's patterns and trends to make forecasts. They are effective for short-term forecasting and complex, less understood relationships [13].

Furthermore, to evaluate the performance of the models and algorithms proposed by the authors, metrics were employed primarily to measure the forecast accuracy of the proposed methods. Fig.5 illustrates the metrics that were used more than once.

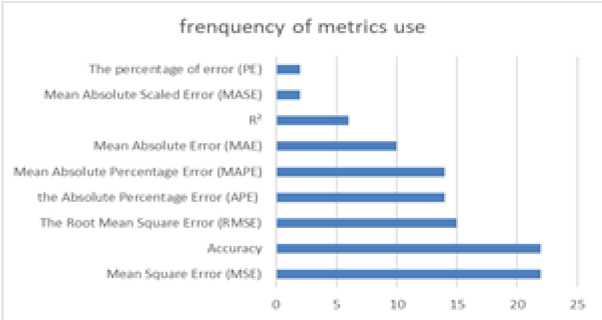

Fig. 5. Metrics used for forecasting accuracy assessment

4.2.2. Forecasting data

The analyzed scientific publications have been categorized based on the type of data, either quantitative or a combination of both quantitative and qualitative. The figure displays the distribution of these papers according to this categorization.

- **Quantitative method**: Based on historical numerical data, and predictions rely on past trends and patterns.
- **Qualitative method**: Rely on subjective judgment, expert opinions, and qualitative data, non-numeric information, to make predictions [34].

Table 4 summarizes the categorization of the data used in the selected research papers, it shows which Times series data was used, whether it is of qualitative and quantitative nature (except historical sales, demand or consumption), and if this data is internal or external to the company.

- **Internal data**: Is the data interne of the enterprise, it includes product's information such as sales, demand, consumption and prices, manufacturing information, Marketing data, etc.
- **External data**: The data extern of the enterprise, such as Economical data: GDP, USD exchange, unemployment rate, etc. Weather data, social media activity, market information, etc.

Several tools are used by researchers for data collection, data analysis, modeling, running the code and testing the forecasting results. The figure indicates the top tools used in the articles analyzed.

Tab. 4. Characteristics of the data used

Reference	Time series Data	Nature of TS Data	Quantitative	Qualitative	Internal	External	Period	Frequency	Prediction horizon	Tools
[35]	x	Historical demand	x	x		x	3 years	Daily	-	-
[37]	x	Historical sales	x		x		2,5 years	Weekly	-	Kaggle Excel R Studio
[38]	x	Historical consumption		x		x	7 years	-	1, 3 and 6 months	Google's cluster data
[39]	x	Historical consumption	x			x	5 years	Quarterly	1 year	-
[16]	x	Historical sales					-	-	3 month	R - studio Python Microsoft Excell
[40]	x	Historical demand	x	x	x	x	5 years	Quarterly	1 year	Statistical Package for Social Sciences (SPSS)
[41]	x	Historical sales	x	x	x	x	5 years	weekly	12 months	R - studio
[34]	x	Historical demand	x	x	x	x	8 years	Monthly	-	MATLAB
[17]	x	Historical sales					19 months	Monthly	-	Python Tensorflow.js
[42]	x	Historical demand					3,5 years	Daily	-	-
[43]	x	Historical	x		x		45	Monthly	-	-

Reference	Time series Data	Nature of TS Data	Quantitative	Qualitative	Internal	External	Period	Frequency	Prediction horizon	Tools
		demand					months			
[44]	x	Historical consumption	x	x	x		-	-	-	R-Studio MATLAB
[10]	x	Historical sales					13 weeks	weekly		-
[45]	x	Historical demand					5 years	Monthly	12 months	-
[46]	x	Historical sales					-	Monthly	3 months	R-studio
[47]	x	Historical Sales rank					-	Daily	1 month	Python
[48]	x	Historical sales		x		x	9 years	Monthly	12 months	Python
[49]	x	Historical demand		x	x		9 years	weekly	-	R-studio
[1]	x	Historical sales	x		x	x	9 years	Monthly	-	SPSS
[50]	x	Historical sales	x	x	x	x	7 years and 3 years	Monthly	6 weeks	-
[51]	x	historical sales					2 years	Monthly	-	CIFAR-100 CIFAR-10
[12]	x	historical sales					6 years	Monthly	-	SPSS
[52]	x	Historical sales	x		x	x	3 years	Monthly	12 months	R-studio
[53]	x	Historical sales	x			x	4 years	Monthly	12 months	wWb crawler Google Trends R-studio
[54]	x	Historical sales and consumption	x		x		5 years	Monthly / Daily	-	-
[55]	x	Historical demand	x		x		3 years	Daily	14 Days / 56 Days	-
[56]	x	Historicl sales	x	x	x		2 years	Daily	2 months	-
[36]	x	Historical demand					1 year	Daily	-	-
[57]	x	Historical sales					5 years	Daily	3 months	Python
[58]	x	Historical sales					6 years	weekly	-	Kaggle
[59]	x	Historical demand	x			x	7 years	Monthly	-	Kaggle Python
[60]	x	Historical demand					-	-	-	Kaggle
[61]	x	Historical sales	x	x	x	x	10 years	Monthly	-	

5. Discussion

5.1. Forecasting methods

The categorization of forecasting methods is mainly based on the approach adopted, i.e. whether the method is solely AI-based, or whether it is hybrid. The analysis of the articles selected shows that 52% of authors used a hybrid approach to generate demand forecasts. While 69% of the models and algorithms used are AI-based, 31% are statistical models.

The most used forecasting method in the articles reviewed is ANN. It was employed in different industries, namely, automotive, apparel & textile and the electronic industry. The aim of ANN is to simulate the human brain functioning, and consist of interconnected nodes (artificial neurons) organized into layers, including an input layer, one or more hidden layers, and an output layer. It includes many models such as MLP, LSTM, RPROP, RNN, CNN, etc.

Five articles based their work solely on the ANN. [37] developed a forecasting model based on multilayer feed-forward neural network with Backpropagation to predict the future demand with precision. The forecasting accuracy and performance achieved surpasses the average performance of most supply chain networks globally by approximately 70% - 80%. As for [34], [40], they present models of ANN to generate demand forecasts using different combinations of several types of data. [52] developed a MLP model more performed comparing to other ones such as ARIMA, Holt-Winters, Exponential smoothing, LASSO, RF and kNN. As regards to [38], the authors used four models of ANN family to predict medicines purchasing, namely MLP, LSTM, CNN and LSTM. Furthermore, [59] built a demand forecasting system with LSTM and compared the results with ARIMA forecasting model, the forecasts obtained by LSTM are close to reality more than ARIMA.

As part of ANN models, RNNs are neural networks that process sequential data using recurrent connections, allowing them to maintain short-term memory of previous sequences. However, traditional RNNs often suffer from vanishing gradient problems when learning long sequences, limiting their ability to capture long-term temporal dependencies. So, LSTMs were introduced to overcome this issue by introducing special memory units that can retain long-term information. In this context, [17], [39] combined RNN and LSTM to forecast the demand. As for [51], they used these two models with Modified-Adam Optimizer to forecast demand more accurately.

Regarding [41], the authors combined ANN with SVM to establish and compare 20 demand forecasting models. Consequently, these studies demonstrate the capability of ANN to generate more accurate demand forecast, and to constitute an alternative to traditional methods.

On the other hand, the use of hybrid approach significantly increases the forecast accuracy and enable the modeling of demand data, incorporating both linear and nonlinear characteristics [2]. So, [35] has hybridized the widely used univariate statistical forecasting model ARIMA with machine learning methods, namely ANN and SVM, to build a hybrid demand forecasting model. The authors conclude that ML methods perform less than traditional models when the training data size is too small. Also, a new forecasting model named "Fuzzy inference system" was developed by [46] combining two systems, the first one using The moving average, Simple exponential smoothing and ARIMA, the second one is composed of ARIMA, ANN and exponential smoothing. Finally, [1] hybridized ANN and SVR with multivariate linear regression analysis and multivariate nonlinear regression analysis to develop a demand forecasting models.

In a context that requires the treatment of a large volumes of historical data and to capture complex patterns and dependencies, ML was widely used in demand forecasting across various industries. In automotive industry [61] hybridizes RF, NN, Stochastic gradient descent and Ensemble learning with LR. And [49] has also cross-breed RF, MLP and SVR with ARIMAX. In server industry, the study proposed an innovative approach based on RF, Holt-Winters exponential smoothing, ARIMA and XGBoost to forecast the demand more accurately [53].

In all the papers analyzed, the authors who used SVR combined it with other AI models such as ANN and RF and hybridized it with statistical models such as ARIMA, ARIMAX, Kernel regression, etc. [1], [12], [43], [48], [49]

Traditional forecasting methods, such as time series, offer clear advantages in simplicity and ease of interpretation, particularly in scenarios with scarce data. In contrast, AI-based methods, utilizing advanced algorithms from machine learning and deep learning, are able to processing and analyzing voluminous datasets. They can identify complex patterns and adjust to new trends. However, they require large amount of data and computational power. Moreover, compared to traditional methods, AI-based forecasting methods are more requires more skills to interpret the results. The decision to use AI versus non-AI techniques depends on the specific forecasting needs, including the complexity of the data, availability of resources, and the necessity for transparency. [15] [19]

In summary, hybridizing statistical models with AI-based models allows harnessing the strengths of each approach to achieve more accurate, robust, and versatile demand forecasts. Furthermore, the publications studied demonstrate that non-conventional forecasting methods are becoming more prevalent, 63% of models and algorithms developed are non-conventional. This is due to rapid evolution of technology, the availability of Big Data, the increasing demand for personalization and real-time responsiveness, and the rise of machine learning and deep learning. These methods offer new possibilities for modeling complex data and providing more accurate forecasts.

The assessment of demand forecasting methods is a critical step in ensuring the accuracy and reliability of forecasting results. Several accuracy metrics are commonly used to evaluate forecasting methods, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics provide quantitative measures of the forecast errors.

5.2. Forecasting data

Demand forecasting involves predicting future demand for products, and time series data help with this by analyzing historical data points collected at regular intervals over time. All the authors based their work on times series data by historical data collection. These data include, among others, historical sales, demand or consumption data, which is collected over a specific time period using different tools. For example [1], [49], [55] extracted historical data from the ERP system.

As for [37], [58], [59], [60], the authors used the online platform Kaggle to download and explore datasets. Also, Google's cluster data was used by [38] for the extraction of the time series dataset. Finally, [53] used Google trends to gather relevant market indicators as external data points for the server sector.

This historical data typically includes timestamps which are essential for understanding the temporal dynamics of demand, identifying seasonal patterns. In the articles reviewed, 48% of time-series data was Monthly, 24% daily and 17% weekly. Consequently, monthly timestamps allow to capture and analyze seasonal patterns and trends in the data such as holiday seasons. Also, it tends to be less noisy and volatile than daily or weekly data. This can make it easier to identify underlying trends and patterns, especially when dealing with longer time series. Furthermore, time series data often requires preprocessing steps to handle missing values, outliers and seasonality. This ensures that the data is accurate and reliable for analysis. In this context, Microsoft excel can be employed for data cleaning, transformation, filtering, integration and data exploring. [16], [37] have used it to process and assemble the dataset as an input.

On the other hand, a third of the articles reviewed employed only historical data such as historical sales, demand or consumption. Relying solely on these latter does not consider external factors like market trends, economic changes, or seasonality. In addition, historical data may not account for sudden market shifts or disruptions, making it challenging to adapt to unexpected events. In addition, it might overlook changes in customer preferences or behavior. Consequently, these limitations result in inaccurate forecasts, so it is recommended to combine historical data with other data like Market related data and predictive analytics which can yield to more robust results.

Data is a crucial component in demand forecasting, the accuracy of the results relies majorly on choosing the most adequate and reliable data. The nature of data as well as its size plays an important role in ensuring the most accurate results. Therefore, analyzing the data used in the selected papers based on their nature and their size is significant for providing a comprehensive synthesis and valuable insight of the reviewed forecasting methods. The nature of data can be classified into various categories; such as qualitative or quantitative data, internal or external data.

Quantitative data relies on historical data and mathematical models to make predictions based on patterns, trends, and relationships within the data. Whereas qualitative data rely on the wisdom and experience of individuals or groups to make informed predictions, especially when historical data is limited, unreliable, or insufficient for accurate forecasting.

Combining quantitative data (numbers, historical sales, etc.) with qualitative data (customer feedback, market research, expert opinion) provides a more comprehensive understanding of demand drivers. Also, it offers insights into customer preferences, sentiments, and behaviors as well as market insight that quantitative data alone may not capture. Leading thus to more accurate forecasts.

More than 50% of the analyzed publications employed a multivariate data input. [34] used qualitative data such as product quality, influence of promotion, customer's satisfaction level, Festivals and holidays periods influence, in addition to historical sales which are considered as a quantitative data.

Internal data refers to the information and data sources that originate from within an organization, it includes historical sales, production records, inventory levels, customer orders, and other internal operational data. As for internal data, it refers to information and data sources that originate from outside an organization, it includes market trends, economic indicators, competitor performance, weather, consumer sentiment, and other external factors that can impact demand. Employing both internal and external data lies in the ability to create more robust and adaptable demand forecasting models. [35] employed data related to search engine queries to obtain more accurate forecasting results.

On the other hand, the time size, which means historical data duration, is a crucial aspect of demand forecasting. It allows identifying recurring patterns, seasonality, and long-term trends in historical demand. Understanding these patterns is vital for making accurate predictions. The choice of data size determines whether the forecast will be short-term or long-term. Short-term forecasts may use recent data, while long-term forecasts may span several years or even decades. The period chosen depends on the specific forecasting goals and the nature of the product or service being forecasted. Longer data periods typically provide more stable and reliable historical data. In the articles reviewed, most authors used historical data duration more than 5 years. Thus, the dimension of data is important not only for the representation of real scenarios but also for the selection of a suitable AI method. Due to the characteristics of demand forecasting, the majority of demand forecasting methods are databased.

6. Conclusion

The industrial sector is confronted to demand variability due to factors such as market fluctuations, seasonality, and unexpected disruptions like the COVID-19 pandemic. This reflects the industry's recognition of the need for agile and adaptable forecasting strategies. Consequently, it is evident that AI-based demand forecasting models have gained significant traction in the industrial sector due to their potential to enhance decision-making processes, optimize inventory management, and ultimately improve supply chain efficiency. These models leverage a variety of AI techniques, including machine learning algorithms, neural networks, and advanced data analytics, to analyze historical data, extract valuable insights, and make accurate predictions about future demand patterns.

This systematic literature review has provided a comprehensive overview of the state-of-the-art AI-based demand forecasting models in the industrial sector published after 2019. It highlights the various AI forecasting methods used in our scope of research as well as the nature of data employed. In conclusion, AI-based demand forecasting models hold great promise for the industrial sector; they are more successful than statistical models. Also, the hybridization of conventional and non-conventional demand forecasting methods offers the potential to enhance operational efficiency, reduce costs, and improve customer satisfaction.

While AI-based forecasting models offer substantial benefits, they are not without challenges. Model interpretability, scalability, and computational resources are some of the key challenges that researchers and practitioners need to address. Additionally, the human-machine collaboration aspect, where domain expertise complements AI-driven insights, is crucial for effective decision-making. Implementing AI-based forecasting in the manufacturing sector faces several hurdles, such as securing quality data, merging AI into existing systems, adapting solutions to diverse operational needs, establishing trust in AI forecasts, and conforming to legal norms.

Therefore, overcoming these requires a comprehensive strategy that balances innovation, organizational change, skill development, and compliance. Ongoing research and development efforts are required to address the aforementioned challenges and to ensure that these models continue to improve to meet the evolving demands of the industrial landscape.

This review has identified a notable gap in forecasting methodologies, specifically the over-reliance on historical data and the underutilization of qualitative information. The prevailing reliance on historical data, while valuable for trend analysis, lacks the integration of qualitative aspects that could enrich the forecasting models with more nuanced, context-specific insights. It emphasizes the need for incorporating qualitative data, such as consumer behaviors or economic indicators, to enhance the depth and relevance of forecasts. the review underscores the opportunity for developing more sophisticated forecasting methodologies that leverage a diverse range of data sources beyond traditional historical records.

Despite this meticulous methodology, it is not without its limitations. As we used several exclusion criteria to delimit the study, it would be interesting to explore AI based demand forecasting in the retail sector, which is a promising sector where demand forecasting is crucial. Furthermore, a complementary study to the present review should be envisaged in order to study the architecture of the most commonly used models, their inputs and outputs.

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Appendix

Tab. 5. demand forecasting models and algorithms

Model/ Algorithm/ Method		Cat 1		Cat 2			Cat 3		Cat 4		Cat 5		Model/ Algorithm/ Method		Cat 1		Cat 2			Cat 3		Cat 4		Cat 5	
	Frequency	Statistical	AI- Based	Baseline	Statistical	ML	Conventional	Non-	linear	Non-linear	Causal	Data-based		Frequency	Statistical	AI- Based	Baseline	Statistical	ML	Conventional	Non-	linear	Non-linear	Causal	Data-based
Artificial Neural Networks (ANN)	18		x			x		x	x	x		x	Harris Hawks optimisation (HHO)	1		x			x		x	x	x		x
Multilayer Perceptron (MLP)	8		x			x		x		x		x	Ensemble of Gradient Boosting	1		x			x		x		x		x
Random Forest (RF)	7		x			x		x		x		x	Gradient Boosting Tree (GBT)	1		x			x	x			x		x
Support Vector Regression (SVR)	7		x			x		x	x	x		x	Invasive Weed Optimization (IWO)	1		x			x		x		x		x
AutoRegressive Integrated Moving Average (ARIMA)	6	x			x		x		x			x	Intermittent Multiple Aggregation Prediction Algorithm (iMAPA)	1		x			x		x		x		x
Neural Network (NN)	5		x			x		x	x	x		x	Modifies-Adam Optimizer	1		x			x		x		x		x
Long Shot-Term Memory (LSTM)	5		x			x		x		x		x	Holt-Winters exponential smoothing	1	x		x			x	x	x			x
Simple exponential smoothing (SES)	5	x		x			x		x		x		Bayesian Structural Time Series (BSTS)	1		x			x		x	x	x		x
Moving averages (MA)	4	x		x			x		x			x	Polynomial neural network	1		x			x		x		x		x
Cultural Algorithm (CA)	3		x			x		x		x		x	Grey Wolf Optimization (GWO)	1		x			x		x	x	x		x
Croston's method (CRO)	3	x		x				x		x		x	Seasonal Linear Regression	1	x		x			x		x		x	
Extreme Learning Machine (ELM)	3		x			x	x		x	x		x	Multiple linear regression analysis	1	x			x		x		x			x
Genetic Programming (GP)	3		x			x		x	x	x		x	Adaptive Boosting (AdaBoost)	1		x			x		x		x		x
Recurrent Neural Network (RNN)	3		x			x	x		x	x		x	k-Nearest Neighbour Regression (kNNR)	1		x			x	x			x		x
Aggregate–Disaggregate Intermittent Demand Approach (ADIDA)	2		x			x		x	x	x		x	Least Absolute Shrinkage and Selection Operator (LASSO)	1	x			x		x		x			x
Auto Regressive Integrated Moving Average with Exogeneous Input (ARIMAX)	2	x			x		x		x			x	Nonlinear Autoregressive Exogenous Neural Network (NARXNN)	1		x			x		x		x		x
Linear Regression (LR)	2	x		x			x		x			x	Multiple nonlinear regression analysis	1	x			x		x			x		x
Convolutional Neural	1		x			x		x	x	x		x	Shallow Neural Networks	1		x			x	x		x	x		x

Model/ Algorithm/ Method		Cat 1		Cat 2		Cat 3		Cat 4		Cat 5		Model/ Algorithm/ Method		Cat 1		Cat 2		Cat 3		Cat 4		Cat 5	
	Frequency	Statistical	AI-Based	Baseline	Statistical	ML	Conventional	Non-	linear	Non-linear	Causal	Data-based		Frequency	Statistical	AI-Based	Baseline	Statistical	ML	Conventional	Non-	linear	Non-linear	Causal	Data-based
Network (CNN)													(SNN)												
Random sampling (RAND)	2	x		x			x		x			x	Elman neural network	1		x			x		x		x		x
Syntetos–Boylan Approximation (SBA)	2	x			x		x					x	Simple Moving Average (SMA)	1	x		x			x		x			x
Support Vector Machine (SVM)	2		x			x		x	x	x		x	Particle Swarm Optimization (PSO)	1		x			x		x		x		x
Radial Basis Function Neural Network (RBF_NN)	2		x			x		x	x	x		x	Deep learning neural network	1		x			x		x	x	x		x
Bayesian Structural Time Series with a Bayesian Classifier	1		x			x		x	x	x		x	Q-Learning algorithm with Extreme Gradient Boosting (QL-XGB)	1		x			x		x		x		x
Ridge regression	2	x			x		x		x			x	Ensemble learning	1		x			x		x		x		x
Koza-style	1		x			x		x	x	x		x	Poisson Regression	1	x			x				x			x
Seasonal Naive	1	x		x			x		x			x	Fuzzy Logic (FL)	1		x			x		x		x		x
Kernel regression	1	x			x		x			x		x	M5 Model tree (M5)	1		x			x		x		x		x
Adaptive Neuro Fuzzy Inference System (ANFIS)	1		x			x		x	x	x	x		Light Gradient Boosting Machine (LightGBM)	1		x			x		x		x		x
Bayesian Neural Network (BNN)	1		x			x		x	x	x		x	Resilient Backpropagation (RPROP)	1		x			x	x		x	x		x
Naïve	2	x		x			x			x		x	Prophet	1	x			x			x		x		x
Classification And Regression Tree (CART)	1		x			x		x		x		x	Roulette Genetic algorithm (GA)	1		x			x		x				x
Cuckoo Search Algorithm	1		x			x		x		x		x	Stochastic gradient descent	1	x				x	x		x	x		x
Double Exponential Smoothing	1	x		x			x		x		x		Extreme Gradient Boosting (XGBoost)	1		x			x		x		x		x

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