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Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting

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ABSTRACT

In today's fast-paced global economy coupled with the availability of mobile internet and social networks, several business models have been disrupted. This disruption brings a whole list of opportunities and challenges for organizations and the domain of supply chain management. Given big data availability, data analytics is needed to convert data into meaningful information, which plays an important role in supply chain management. One of the disruptive data analytics techniques that are predicted to impact growth, employment, and inequality in the market is automation of knowledge work, better known as machine learning. In this paper, we focused on comprehensively overviewing machine learning applications in demand forecasting and underlying its potential role in improving the supply chain efficiency. A total of 1870 papers were retrieved from Scopus and Web of Science databases based on our string query related to machine learning. A reduced total of 79 papers focusing on demand forecasting were comprehensively reviewed and used for the analysis in this study. The result showed that neural networks, artificial neural networks, support vector regression, and support vector machine were among the most widely used algorithms in demand forecasting with 27%, 22%, 18%, and 10%, respectively. This accounted for 77% of the total reviewed articles. Most of the machine learning application (65%) was applied in the industry sector, and a limited number of articles (5%) discussed the agriculture sector. This paper's practical implication is in exposing the current machine learning issues in the industry to help stakeholders and decision-makers better plan transformation actions.

Keywords: *disruptive technology, machine learning, supply chain management, demand forecasting*

1. INTRODUCTION

Today's advancement in technology, coupled with the availability of mobile internet and social networks, has disrupted several business models. This disruption brings a whole list of opportunities and challenges for organizations and the domain of supply chain management (Aamer, 2018; Bower & Christensen, 1996; Huddiniah & ER, 2019). In an attempt to improve the supply chain's total generated value, it is predicted that disruptive technologies would influence the development of new techniques, principles, and models in supply chain management of the industries (Ivanov *et al.*, 2019). Some of the supply chain management domain opportunities include better visibility and traceability of products and services along the supply chain, and some of the challenges include cybersecurity, technology learning curves, and adaptability. Another important consequence of today's technology, and the availability of mobile technology and the Internet of Things (IoT), is the increased data collection volume, which is referred to as big data. Big data is known by the five V's: Volume, Velocity, Variety, Veracity, and Value (Affia *et al.*, 2019; Jeble *et al.*, 2018). Given big data availability, data analytics is needed to convert data into meaningful information, which plays an important role in supply chain management. Data analytics can be defined as using statistical and mathematical tools to analyze available data and produce meaningful information for decision-makers (Jeble *et al.*, 2018).

One of the disruptive data analytics techniques that is predicted to impact growth, employment, and inequality in the market is automation of knowledge work, better known as machine learning (Leipziger *et al.*, 2016; Manyika *et al.*, 2015; Yani *et al.*, 2019). Various algorithms are used in machine learning, which is generally divided into two categories: supervised and unsupervised machine learning algorithms. Machine learning, which is viewed as a disruptive technology, has rapidly evolved in recent years to optimize the process and efficiency in supply chain management. According to research, machine learning could be applied in several stages of supply chain management.

More specifically, it could be used to generate better forecasting models in the presence of big data (Bousqaoui *et al.*, 2018; Raguseo, 2018).

Supply chain management focuses on creating value for the customers by optimizing the flow of products and services through the supply chain effectively and efficiently (Aamer, 2018; Aamer and Sawhney, 2004; Chopra and Meindl, 2013; Sahara *et al.*, 2019; Yani *et al.*, 2019). However, one of the most dynamic issues in supply chain management is the quest of having reliable customer demand forecasting (Chong *et al.*, 2017)**.** One of the most common consequences of poor demand forecasting is known as the Bullwhip Effect (Norrman and Naslund, 2019). Therefore, from the perspective of economic growth, employment, and inequality in the market is predicted to apply disruptive technology, such as machine learning, to supply chain management. To contribute to Indonesia's optimistic and critical strategic plan toward industry revolution 4.0 by 2025 (BKPM, 2019), important tools needed in areas related to the Indonesian government strategic plan's focus sectors should be pinpointed. This research focused on comprehensively overviewing machine learning applications in demand forecasting and underlying its potential role in improving the supply chain efficiency. Even though there are other reviews on data analytics and machine learning, there are limited reviews on machine learning algorithms in demand forecasting. In this research, we provided an overview of machine learning application in demand forecasting for the supply chain by answering the following questions:

- RQ1: What are the machine learning algorithms and techniques used in demand forecasting in the supply chain?
- RQ2: What are the trends and gaps in the literature reviewed?

The remainder of this research is organized as follows: Section 2 presents background information about the study. Section 3 discusses the methodology used in this paper. In section 4, we present the overview results and discuss the literature gaps. Section 5 concludes the research with future research directions.

2. MACHINE LEARNING AND DEMAND FORECASTING

Research in operations and supply chain management has proved the importance and big role supply chain management plays in many organizations' sustainability, especially in today's disruptive era. For the past fifteen years, historical data has shown us that several organizations were forced out of business because of misreading the market signs and not being able to keep up with today's rapid development in technology and rapid growth in consumer demand and expectations. For example, Blockbuster in the USA went out of business for not being able to keep up with the technology trend and reading consumer behavior and demand. Other successful world-class organizations, such as Walmart in the USA, still clinch the top ranking among companies in the USA for reasons including the efficient supply chain network and its management. Other similar organizations in the context of Asia in general, and Indonesia in particular, include organizations such as Tokopedia, an e-commerce company similar to Amazon in the USA, which leverage emerging technology in improving logistics, fulfillment, payment to anticipate and forecast consumer demand and have innovative supply chain management operations. One can claim that the more efficient, transparent, resilient, and responsive the supply chain, the better revenue, and profit the organization can reap.

One critical factor of supply chain management efficiency is the accuracy of demand forecasting, as it plays an essential role in reducing the Bullwhip Effect (Chong *et al.*, 2017). Therefore, there is a need to develop reliable demand forecasting models to make better and more accurate predictions. Machine learning is one promising disruptive tool that could be utilized in developing better demand forecasting models than what is being used in supply chain management currently. Machine learning is a subset of artificial intelligence where the machine learning algorithm acts or performs the task without being explicitly programmed. The machine can learn automatically from the past raw data to generate predictive models based on predesigned algorithms. In general, there are two types of learning algorithms: supervised and unsupervised learning. Supervised machine learning algorithms learn from labeled data: input and output. The algorithm is responsible for finding the relationship between the input and the output and stops learning when it achieves an acceptable performance level.

On the other hand, there is only input data and no corresponding output data in unsupervised learning. The algorithm aims to find patterns and structure to learn more about the given data (Goodfellow *et al.*, 2016). Supervised and unsupervised learning algorithms are used mainly for four types of tasks: regression, classification, clustering, and association (Kone and Karwan, 2011). Various algorithms are used for machine learning, including, among others, neural networks, support vector machines, regression, decision trees, random forests, and k-means algorithms. Each algorithm has its advantages and disadvantages in implementation, depending on the case of the business. It is not in the scope of this research to discuss each machine learning topic but to overview which topic has been addressed in the context of demand forecasting.

Recently, machine learning has been utilized in different stages of supply chain management in the industry. Some of the most recent research addressed the application of machine learning, such as Bousqaoui *et al.* (2018), Feki *et al.* (2016), Varela (2015), and Bonnes (2014). Others have specifically presented an overview of machine learning applications in demand forecasting, such as Carbonneau *et al.* (2008). Nonetheless, there is still a lack of focused overview studies of machine learning applications in the demand forecasting area. The following sections present a comprehensive overview of machine learning applications demand to forecast related to three main sectors in Indonesia. According to the World Bank, agriculture, industry, and service sectors are the top three of Indonesia's business sectors (The World Bank, 2019). The agriculture sector includes forestry, hunting, fishing as well as cultivation of crops and livestock production. The industry sector includes mining, manufacturing, construction, electricity, water, and gas. Lastly, the services sector has businesses such as hotels and restaurant services, transport, government, financial, professional, and personal services such as education, healthcare, and real estate services. Indonesia is the secondlargest rubber producer in the world. Other major crops include sugarcane, rice, coffee, palm oil, and other crops that make up the agriculture business sector contribute 13.14% of the country's GDP. Industry sectors such as the manufacturing of textiles, cement, electronic products, rubber tires, and others contribute around 39.37% of Indonesia's GDP. Meanwhile, the service sector, such as financial institutions, transportations, communications, has a higher contribution among the other two sectors. The service sector contributes approximately 43.6% of the total Indonesian GDP (The World Bank, 2019).

3. METHODOLOGY

This paper aims to explore and consolidate the past and current findings in the implementation of machine learning for demand forecasting through a comprehensive analysis of the related literature. Given the literature review nature of this research, we followed the systematic literature review method in conducting our overview as it is more suitable and rigorous when using digital databases to retrieve, screen, and synthesize previous research (Okoli and Schabram, 2010; Webster and Watson, 2002). Our research strategy was carried out using the following search strings related to our research questions: *(Machine learning OR linear regression OR neural network OR support vector machine OR deep learning) AND (demand forecasting)*, which match the keyword string available in the title OR abstract OR keywords of previous studies. The search for articles was limited to the last ten years, from 2010 to 2019. Our literature search was limited to only those databases, journals, and conferences with a good academic reputation. Due to the recent emergence of machine learning applications in supply chain management, we had to expand our searched databases to include reputable databases, journals, and conferences with credible and sound academic reputations. We used the Scopus and Web of Science databases as our sources for retrieving the relative studies.

In selecting the studies to be reviewed, we retrieved all papers written in English that met our search strings and keywords. The next step for screening consisted of papers that proposed any demand forecasting model. The final list of papers retrieved from the database on the string queries was 1870 papers as illustrated in **Figure 1**: 558 papers from Science direct, 316 papers from Emerald, 957 papers from Taylor & Francis, 34 papers from IEEE, and five papers from. After that, we conducted a screening process of the retrieved papers to search the title and abstract of 1870 papers to find if the papers addressed our research question of the implementations of machine learning and demand forecasting in supply chain management. Given many papers, we reviewed the titles and abstracts as a more efficient screening process, and the total was reduced to 124 related studies. We conducted a more systematic content analysis of the most relevant and remaining total of 77 papers.

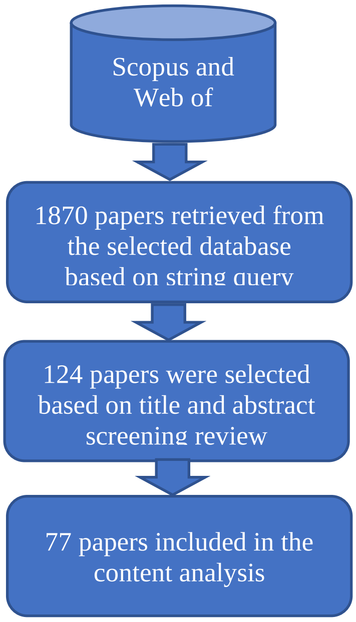

Figure 1 The systematic literature review processes

4. RESULTS AND DISCUSSION

The total number of published papers in the last ten years in machine learning and demand forecasting has fluctuated. However, there is a noticeable and relatively significant increase in the previous two years, as depicted in **Figure 2**. 34 papers published in 2018 and 2019 alone counted for 44% of the total publications in the last ten years. Another important finding is that most of the published papers in machine learning and demand forecasting focused on the industry sector with 65% and followed by the service and agriculture with 30% and 5%, respectively. The summary results of our review are presented in **Table 1** and **Table 2**. **Table 1** shows the distribution of published papers by sector and the Machine Learning algorithm used. **Table 2** further summarizes the distribution of articles by the type of machine learning algorithm used.

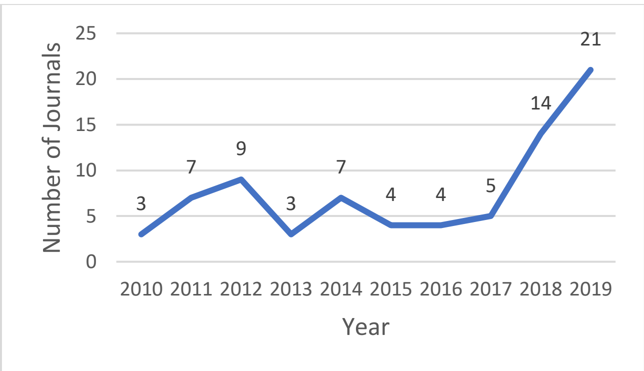

Figure 2 The trend of published papers in machine learning applications in demand forecasting

Table 1 Article distribution by industry sector and machine learning algorithm used

Machine Learning Algorithm	References	Total # of Papers	% of Algorithm	% Sub-sector	% Sector
Agriculture Sector		**4**			**5%**
Support Vector Machine	(Bolandnazar *et al.*, 2019; Du *et al.*, 2013; Zhu *et al.*, 2019)	3	75%		
Artificial Neural Network	(Puchalsky *et al.*, 2018)	1	25%		
Industry Sector		**51**			**65%**
Energy Demand		**12**		**24%**	
Artificial Neural Network	(Bekkari and Zeddouri, 2019; Kialashaki and Reisel, 2014; Saloux and Candanedo, 2018)	3	25%		
Neural Network	(Ahmad and Chen, 2018; Mason, Duggan, Barrett, *et al.*, 2018)	2	17%		
Decision Tree	(Saloux & Candanedo, 2018)	1	8%		
Linear Regression	(Spencer and Al-Obeidat, 2016)	1	8%		
Random Forest	(Huang, Liang, *et al.*, 2019)	1	8%		
Reinforcement Learning	(Wee and Nayak, 2019)	1	8%		
Support Vector Machine	(Saloux and Candanedo, 2018; Shi *et al.*, 2012)	2	17%		
Support Vector Regression	(Chou and Ngo, 2016)	1	8%		
Electricity Demand		**20**		39%	
Artificial Neural Network	(Badri *et al.*, 2012; Chu *et al.*, 2011; Çunkaş and Altun, 2010; Ertugrul, 2016; Eseye *et al.*, 2019; Saxena *et al.*, 2019)	6	30%		
Support Vector Regression	(Al-Musaylh *et al.*, 2018; Elattar *et al.*, 2010; Maldonado *et al.*, 2019; Nagi *et al.*, 2011)	4	20%		
Deep Learning	(Qiu, Zhang, *et al.*, 2017)	1	5%		
Extreme Learning Machine	(Liu *et al.*, 2019)	1	5%		
Random Forest	(Johannesen *et al.*, 2019)	1	5%		

Table 2 Article distribution by industry sector and machine learning algorithm used (cont')

Machine Learning Algorithm	***References***	***Total # of Papers***	***% of Algorithm***	***% Sub-sector***	***% Sector***
Support Vector Machine	(Huang, Liang, *et al.*, 2019)	1	5%		
Gaussian Process	(Alamaniotis *et al.*, 2012)	1	5%		
Neural Network	(Hanmandlu and Chauhan, 2011; Khosravi and Nahavandi, 2014; Lou and Dong, 2013; Nose-Filho *et al.*, 2011; Quan *et al.*, 2014)	5	25%		
Water Demand		**9**		18%	
Artificial Neural Network	(Kofinas *et al.*, 2014; Vijai and Bagavathi Sivakumar, 2018)	2	22%		
Extreme Learning Machine	(Mouatadid and Adamowski, 2017)	1	11%		
Neural Network	(Tiwari and Adamowski, 2017a)	1	11%		
Support Vector Regression	(Braun *et al.*, 2014; Brentan *et al.*, 2017; Herrera *et al.*, 2010, 2011)	4	44%		
Support Vector Machine	(Candelieri *et al.*, 2015)	1	11%		
Natural Gas Demand		**3**		6%	
Extreme Learning Machine	(Izadyar *et al.*, 2015)	1	33%		
Neural Network	(Hribar *et al.*, 2019)	1	33%		
Support Vector Regression	(Beyca *et al.*, 2019)	1	33%		
Cellular Network Demand		**1**		2%	
Deep Learning	(Fang *et al.*, 2018)	1	100%		
Apparel Industry Demand		**2**		4%	
Artificial Neural Network	(Aksoy *et al.*, 2012, 2014)	2	100%		
Heat Demand		**1**		2%	
Neural Network	(Sala-Cardoso *et al.*, 2018)	1	100%		

Table 3 Article distribution by industry sector and machine learning algorithm used (cont')

Machine Learning Algorithm	References	Total # of Papers	% of Algorithm	% Sub-sector	% Sector
Electronics Demand		**1**		2%	
Neural Network	(Chen, Yeh, *et al.*, 2012)	1	100%		
Residential Demand		1		2%	
Neural Network	(Percy *et al.*, 2018)	1	100%		
Coal Demand		1		2%	
Artificial Neural Network	(Jebaraj *et al.*, 2011)	1	100%		
Services Sector		**24**			**30%**
Tourism Demand		**11**		**46%**	
Neural Network	(Claveria *et al.*, 2015; Huarng *et al.*, 2012; Yao *et al.*, 2018; Yu *et al.*, 2017)	4	36%		
Artificial Neural Network	(Golshani *et al.*, 2018; King *et al.*, 2014)	2	18%		
Extreme Learning Machine	(Sun *et al.*, 2019)	1	9%		
k-Nearest Neighbor	(Rice *et al.*, 2019)	1	9%		
Random Forest	(Cheng *et al.*, 2019)	1	9%		
Gaussian Process	(Wu *et al.*, 2012)	1	9%		
Support Vector Regression	(Hong *et al.*, 2011)	1	9%		
Transportation Demand		**9**		**38%**	
Support Vector Regression	(Plakandaras *et al.*, 2019; Zhao and Mi, 2019)	2	22%		
Adaptive-neuro-fuzzy classifier	(Minal *et al.*, 2019)	1	11%		
Back Propagation Network	(Gao and Lee, 2019)	1	11%		
Deep Learning	(Ke *et al.*, 2017)	1	11%		

Table 4 Article distribution by industry sector and machine learning algorithm used (cont')

Machine Learning Algorithm	References	Total # of Papers	% of Algorithm	% Sub-sector	% Sector
Neural Network	(Chen, Kuo, *et al.*, 2012; Xu *et al.*, 2018; Ye *et al.*, 2012)	3	33%		
Random Forest	(Ferrara *et al.*, 2019)	1	11%		
Healthcare Service Demand		**3**		**13%**	
Neural Network	(Jiang *et al.*, 2018)	2	67%		
XGBoost	(Klute *et al.*, 2019)	1	33%		
Banking Service Demand		**1**		**4%**	
Neural Network	(Joseph *et al.*, 2013)	1	100%		
Service-Oriented Manufacturing Demand		**1**		**4%**	
Support Vector Machine	(Cao *et al.*, 2017)	1	100%		

Table 2 Distribution of articles by machine learning algorithm used

Machine Learning Algorithm	References	Number of Articles	% From Total
Neural Network	(Ahmad *et al.*, 2018; Chen, Yeh, *et al.*, 2012; Chen, Kuo, *et al.*, 2012; Claveria *et al.*, 2016; Hanmandlu and Chauhan, 2011; Hribar *et al.*, 2019; Huarng *et al.*, 2012; Jiang *et al.*, 2018; Joseph *et al.*, 2013; Khosravi and Nahavandi, 2014; Lou and Dong, 2013; Mason, Duggan and Howley, 2018; Nose-Filho *et al.*, 2011; Percy *et al.*, 2018; Quan *et al.*, 2014; Sala-Cardoso *et al.*, 2018; Tiwari and Adamowski, 2017b; Xu *et al.*, 2018; Yao *et al.*, 2018; Ye *et al.*, 2012; Yu *et al.*, 2017)	21	27%
Artificial Neural Network	(Aksoy *et al.*, 2012, 2014; Badri *et al.*, 2012; Bekkari and Zeddouri, 2019; Chu *et al.*, 2011; Çunkaş and Altun, 2010; Ertugrul, 2016; Eseye *et al.*, 2019; Golshani *et al.*, 2018; Jebaraj *et al.*, 2011; Kialashaki and Reisel, 2014; King *et al.*, 2014; Kofinas *et al.*, 2014; Puchalsky *et al.*, 2018; Saloux and Candanedo, 2018; Saxena *et al.*, 2019; Vijai and Bagavathi Sivakumar, 2018)	17	22%
Support Vector Regression	(Al-Musaylh *et al.*, 2018; Beyca *et al.*, 2019; Braun *et al.*, 2014; Brentan *et al.*, 2017; Chou and Ngo, 2016; Elattar *et al.*, 2010; Herrera *et al.*, 2010, 2011; Hong *et al.*, 2011; Maldonado *et al.*, 2019; Nagi *et al.*, 2011; Plakandaras *et al.*, 2019; Zhao and Mi, 2019)	13	17%

Table 2 Distribution of articles by machine learning algorithm used (cont')

Machine Learning Algorithm	References	Number of Articles	% From Total
Support Vector Machine	(Bolandnazar *et al*., 2019; Candelieri *et al*., 2015; Cao *et al*., 2017; Du *et al*., 2013; Huang, Liang, *et al*., 2019; Saloux and Candanedo, 2018; Shi *et al*., 2012; Zhu *et al*., 2019)	8	10%
Extreme Learning Machine	(Izadyar *et al*., 2015; Liu *et al*., 2019; Mouatadid and Adamowski, 2017; Sun *et al*., 2019)	4	5%
Random Forest	(Cheng *et al*., 2019; Ferrara *et al*., 2019; Huang, Yuan, *et al*., 2019; Johannesen *et al*., 2019)	4	5%
Deep Learning	(Fang *et al*., 2018; Ke *et al*., 2017; Qiu, Ren, *et al*., 2017)	3	4%
Adaptive-neuro-fuzzy classifier	(Minal, Sekhar, & Madhu, 2019)	1	1%
Back Propagation Network	(Gao & Lee, 2019)	1	1%
Decision Tree	(Saloux & Candanedo, 2018)	1	1%
Gaussian Process	(Alamaniotis *et al*., 2012)	1	1%
k-Nearest Neighbor	(Rice *et al*., 2019)	1	1%
Linear Regression	(Spencer & Al-Obeidat, 2016)	1	1%
Reinforcement Learning	(Wee & Nayak, 2019)	1	1%
XGBoost	(Klute *et al*., 2019)	1	1%
	Total	78	**100%**

According to **Table 1**, most of the research presented in the literature focused on applying machine learning algorithms in the industry sector, especially for the electricity and energy demand with 39% and 24%, respectively. A minimal number of papers addressed the demand forecasting in the manufacturing category, such as the apparel industry (4%) and electronics (2%), which accounted for the least percentage. This could be due to the difficulty facing manufacturers in adopting new technologies and presents a gap in the literature that needs to be further investigated. Artificial neural networks and neural networks are the most used algorithms among all industry sub-sectors, with percentages ranging between 17% and 100%, as presented in **Table 1**. This supports the claim of authors that artificial neural networks and neural networks offer better demand forecasting accuracy. They are also supported by the total number of articles in **Table 2**. **Table 2** shows that both artificial neural networks and neural networks accounted for 48% of the machine learning applications' algorithms in demand forecasting for the last ten years.

With the increased technology applications and widespread e-services, we see evidence of increased utilization of machine learning in this sector. According to our review, the service sector came in second place after the industry sector, with a total percentage of 30% from the general application of machine learning in demand forecasting in the supply chain. More machine learning algorithms are evident in the tourism and transportation subsectors with a large total percentage of 84%. Like the industry sector, neural and artificial networks were among the highest algorithms. Besides, support vector regression was used in demand forecasting. This could be to the fast-paced development of several online applications that offer services to customers where big data is collected and used to targeted demand forecasting and targeted marketing, especially in social media networks.

The lowest percentage of machine learning applications in demand forecasting is in the agriculture sector, with 5%. This is an alarming percentage for the low utilization of data analytics and machine learning algorithms in a critical and important national economy industry. This could be due to the lower level of technology implementation and integration in the agriculture industry. This is one of the literature gaps that researchers and practitioners need to address to improve the agriculture sector, especially in countries such as Indonesia, where this sector plays a significant role in the country's economic development.

The list of machine learning algorithms and techniques used in demand forecasting in the supply chain are presented in **Table 2**. The top algorithms used in demand forecasting, based on our review, were neural network, artificial network, support vector regression, and support vector machine with 27%, 22%, 18%, and 10%, respectively. This accounted for 77% of the total reviewed articles. The remaining algorithms ranged between 1% and 5%, which indicated the unpopularity of these algorithms in each of the three main sectors and their subsectors. This is in no way an indication of these algorithms' un-applicability in demand forecasting but merely the popularity of what has been applied. Some researchers conducted a comparative analysis for some of the least popular machine learning algorithms to give some insight into the suitability and applicability of these algorithms. For example, Izadyar *et al.* (2015) compared several machine learning algorithms such as artificial neural networks, neural networks, and extreme machine learning. The authors claimed stated that an extreme machine learning algorithm has better performance in terms of accuracy. Similarly, Huang *et al.* (2019) compared XGBoost, extreme learning machine, linear regression, and support vector regression and found that the support vector regression algorithm produced more accurate results, among others. This calls for further investigation of the least popular algorithms and their applicability in the sectors and perhaps other sectors.

We can conclude that machine learning algorithms could provide better accuracy and less computational cost for demand forecasting than traditional forecasting models. This finding is supported by some of the reported studies in the literature, including Golshani *et al.* (2018), Jiang *et al.* (2018), Saloux & Candanedo (2018), Cheng *et al.* (2019), Saxena *et al.* (2019). Besides, based on our review, one of the trends in the machine learning applications in demand forecasting included is the application of neural network algorithms when using machine learning in demand forecasting in the context of supply chain management. This could be due to better neural network performance in forecasting accuracy compared to other algorithms such as linear regression and extreme learning machine algorithms. This is by no means an indication that neural network algorithms in machine learning always outperform others. Machine learning algorithms could perform better in one situation but not in others, depending on data and situation (Goodfellow *et al.*, 2016). Another trend is that most of the machine learning application is in the industry sector, and the gap is in the agriculture sector. This calls for more research needed in the agricultural area to improve data analytics' efficiency by implementing machine learning in demand forecasting to enhance the efficiency of supply chains. This is important for economic growth for countries such as our country of interest, Indonesia, where both sectors contribute significantly to the national GDP.

5. CONCLUSION

This paper addressed two main questions related to machine learning applications and techniques used in demand forecasting in the supply chain. Also, we identified some of the associated trends and gaps in the machine learning literature review. Our study classified the applications based on three business sectors, namely, agriculture, industry, and service sectors. Based on our analysis, we concluded that machine learning algorithms could provide better accuracy and less computational cost for demand forecasting than traditional forecasting models. Also, based on our review, one of the trends in the machine learning applications in demand forecasting included is the application of neural network algorithms when using machine learning in demand forecasting in the context of supply chain management. Most of the machine learning applications were found in the industry sector, and limited machine learning applications were found in the agriculture sector. This calls for more research needed in the agricultural area to improve data analytics' efficiency by implementing machine learning in demand forecasting to enhance the efficiency of supply chains. This is important for economic growth for countries such as our country of interest, Indonesia, where both sectors contribute to the national GDP.

Future research should also focus on applying machine learning in the service sector in both the transportation and health industry. Given the current global disruption of the supply chain and economy in general, due to the pandemic known as COVID-19, we believe that machine learning could play a significant role in creating more efficient and transparent collaborative planning, forecasting, and replenishment along the supply chain.

This study contributes to the supply chain management body of knowledge. It also serves as a foundational study to help other researchers address the research gap by expanding machine learning applicability in other vital sectors such as agriculture. The study also contributes practically to managers and decision-makers or organizations for what has been done to transition from traditional forecasting models and use machine learning algorithms to seek better and more accurate predictions.

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