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Implementation Of Machine Learning in Demand Forecasting: A Review of Method Used in Demand Forecasting with Machine Learning

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Abstract. Demand Forecasting is essentials in making production decisions. Demand forecasting accuracy affects supply chain management and can reduce its costs. The development of information technology, especially artificial intelligence, has many benefits in many industrial sectors. The development of artificial intelligence is also applied to demand forecasting. The development of Artificial Intelligence technology in forecasting can produce better accuracy than conventional methods that do not use Artificial Intelligence. The use of machine learning in demand forecasting is in various industrial sectors ranging from small-scale industry to large-scale industry. This article will discuss research on the use of machine learning in demand forecasting for the things discussed, including machine learning models, data processing methods, and research variables. The purpose of this review is to see a comparison of the accuracy of each model, method, and variable used in demand forecasting using machine learning. The results of the review show that the characteristics of different product fluctuations require a different demand forecasting model approach. An appropriate approach can produce higher forecasting accuracy. Mistake in choosing a demand forecasting model can reduce the accuracy of demand forecasting. The demand forecasting model must also need to be updated to improve accuracy.

Keyword: Machine Learning, Demand Forecasting

Abstrak. *Forecasting Permintaan merupakan hal yang penting dalam mengambil keputusan produksi. Keakuratan forecasting permintaan berpengaruh terhadap manajemen rantai pasok dan dapat mengurangi biaya manajemen rantai pasok. Perkembangan teknologi informasi khususnya artificial intelligence telah banyak memberi manfaat dalam banyak sektor industri. Perkembangan artificial intelligence juga diterapkan pada forecasting permintaan. Perkembangan teknologi Artificial Intelligence dapat menghasilkan forecasting yang lebih akurat dari pada metode konvensional yang tidak menggunakan Artificial Intelligence. Penggunaan machine learning dalam forecasting permintaan digunakan dalam berbagai sektor industri mulai dari industri skala kecil sampai industri skala besar. Artikel ini akan membahas penelitian mengenai penerapan machine learning dalam forecasting permintaan. Hal yang dibahas.meliputi model machine learning, metode pengolahan data, dan variable penelitian. Tujuan dari review ini adalah untuk melihat perbandingan akurasi dari setiap model, metode, dan variabel yang digunakan dalam forecasting permintaan menggunakan machine learning. Hasil review menunjukan bahwa kharakteristik fluktuasi produk yang berbeda membutuhkan pendekatan model forecasting permintaan yang berbeda. Pendekatan yang sesuai dapat menghasilkan akurasi forecasting yang lebih tinggi. Kesalahan dalam memilih model forecasting permintaan dapat*

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mengurangi akurasi forecasting permintaan. Model forecasting permintaan juga harus selalu diupdate untuk meningkatkan akurasi.

Kata Kunci: Machine Learning, Peralaman Permintaan

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1. Introduction

Demand forecasting is the thing that is challenging for producers because it affects operational decision-making [25]. Yue et al. [28], Bertaglia [3], Martinez, et al. [19], and Arvan et al. [2] stated that Demand forecasting is an essential part of supply chain management, which affects competitiveness and profitability, and provides important information for buying decisions, production, inventory levels, logistics, finance, and marketing.

Unsold goods are a waste that can be reduced by accurate demand forecasting; accurate demand forecasting can also reduce the level of safety stocks [8]. Carter et al. [5] stated that the problem of failing to meet consumer demand due to the unavailability of inventory could be more difficult for businesses in terms of income, customers, trust, and stock market prices if controlled immediately and intelligently. On the other hand, if managed intelligently, it can reduce expenses related to logistics.

The machine learning method is an algorithm to recognize data patterns without knowing how the data is formed [9]. Mitra [1] stated that with the advent of Industry 4.0, the industry chose to predict customer demand by applying a machine learning forecasting classifier algorithm to overcome inaccurate demand forecasting. Elcio Tarallo et al. [29] stated the critical role of machine learning in forecasting demand. The researchers discuss the higher value of forecasting accuracy using machine learning compared to not using machine learning.

According to Brynjolfsson, Hitt, & Kim [4]; McAfee & Brynjolfsson [20], by making decisions based on data, the top three companies in their field are 5% more productive and 6% more profitable than companies in the same field. Puchalsky [23] stated Human hard to decide when appropriate forecasting models are used because they need many variables to achieve smaller errors, indicating that support from automated tools is required. Kuo [12]; Lachtermacher & Fuller [14] stated that the forecasting method with Artificial Neural Network has better performance than conventional forecasting methods.

One of the challenges in forecasting is changing market conditions and changing demand. Machine learning methods can reduce the risk of demand uncertainty because machine learning methods perform data recognition continuously and automatically with the help of computers. Machine learning has many models to choose from. Each model has a different level of accuracy. The difficulty faced in demand forecasting using machine learning is to determine the most accurate model. In this research review, the model used in previous research will be discussed to determine the level of accuracy produced.

2. Review Method

The research review was carried out in terms of the machine learning model used in Demand Forecasting, the data processing methods used in the research, and the variables used in the research. A machine learning model is a model that is selected in the software to determine the equation that best fits the analyzed data. Software that is usually used for machine learning is Python. Data processing methods are the stages passed in machine learning data processing. Each research may have a different data processing method. Research variables are data in research that are variable in nature and affect the value of forecasting accuracy.

In this review article, we will discuss every accuracy produced by the forecasting model. This article discusses the models used by each researcher along with the forecasting accuracy. Each model used will be compared for its level of accuracy. The accuracy measurement used by each researcher is different but still suitable for measuring demand forecasting accuracy. The discussion is carried out on every method used by previous researchers in achieving high forecasting accuracy, including the selection of machine learning models, the selection of variables, and the data processing methods used.

3. Research Reviews

In Nikolas U. Moroff et al. study [21], an experiment was conducted to forecast demand with six models and five different products. The model used can be seen in Figure 1. The results of these experiments are that the ETS model has the highest accuracy for some products, and for other products, the machine learning model has higher accuracy.

Prod.	Stat. Models		ML Models		DL Models	
	SARIMAX	ETS	RF	XGBoost	LSTM	MLP
A	4.341	6.786	10.817	9.706	3.932	6.172
B	8.109	3.219	8.777	8.712	4.658	3.656
C	14.237	13.513	25.477	25.978	24.539	11.591
D	1.909	1.879	3.902	3.983	2.633	2.313
E	1.010	1.208	1.439	729	1.034	954

Figure 1 Forecasting Errors (RMSE) in the Research of Nikolas U. Moroff et al. [21]

According to Nikolas U. Moroff et al. [21], the model with the highest accuracy value is different for different products. The shortcoming in the journal Nikolas U. Moroff et al. [21] is that it only uses one variable, demand history, while additional variables can improve forecasting accuracy. The model used in this study is a machine-learning regression model.

The choice of a machine learning model affects forecasting accuracy. The forecasting model consists of regression and clustering. According to Jakob Huber [10], the machine learning demand forecasting model with the clustering model has a high accuracy value. However, there is still the possibility of higher accuracy than other forecasting models besides those used in his research. The forecasting model used in Jakob's research is a machine learning clustering forecasting model.

Method	MASE	MAE	Rank
MLP-CL (max)	1.00	1.00	1.55 (0.49)
MLP-CL (median)	**0.94**	**0.93**	**1.45 (0.49)**
LSTM-CL (max)	1.00	1.00	1.56 (0.49)
LSTM-CL (median)	**0.94**	**0.93**	**1.44 (0.49)**

Figure 2 Forecasting Accuracy Values in Jakob Huber's Research [10]

There are many models used in demand forecasting research. Still, according to Caruana & Niculescu-Mizil [6], machine learning models have the best performance, including random forest, boosting, support vector machines (SVM), and neural networks, which have much better performance compared to simpler models such as decision trees, nave Bayes, or decision rules.

In the research of Chi Jie Lu& Ling-Jing Kao [13], the machine learning model is Extreme Learning Machine (ELM). ELM is a part of single-layer neural networks. In the research of F.L. Chen [7], the machine learning model used is Gray Extreme Machine Learning (GELM). GELM is an extension of the machine learning neural network model.

Looking at the data processing side, as was done in the research of Chi Jie Lu & Ling-Jing Kao [13], data processing is carried out first before carrying out the machine learning process, where the data is grouped first before selecting the model. The grouping of data or products is based on the assumption that certain product groups have different accuracy results when forecasting is carried out with the same model. Paolo Mancuso et al. [18] tested the forecasting model for each data hierarchy and found that lower-level data had higher noise levels. An example of a data hierarchy is product demand at the sub-district, city, and province levels.

The selection of the correct variables can improve demand forecasting accuracy. The choice of the correct variables can improve demand forecasting accuracy. In Takashi Tanizaki's research [24], the forecasting variables used are sales, restaurant locations, and the number of weekly and monthly sales days. In addition to the variables mentioned in Tanizaki's research [24], several variables are used in forecasting demand, including sales competitors, price, and weather data, as in the research of F.L. Chen [7].

In a study conducted by Jakob Huber et al. [10], sales and calendric special days data are used in a year. The accuracy value obtained in Jakob Huber et al. [10] research can be seen in Figure 2. In Shaohui Ma's research [15], the forecasting variable used is promotional activities, price, and displays. Shuojiang Xu research [27], the forecasting variable used is disease information from search engines to predict the demand for medical tools. Forecasting demand with machine learning is carried out in the industrial world and health world, as in Shoujiang Xu's research [27].In Kevin W. Walker's research [26], forecasting with machine learning is used in libraries.

Model type	MAD	MSE	Training time (CPUs)
GBPN	0.24872	0.05203	14.92
GMFLN	0.22096	0.04891	6.210
GELM	**0.16008**	**0.04114**	**0.031**

Figure 3 Forecasting Error Values in F.L. Chen's Research [7]

Comparison group	Methods	Company A		Company B	
		MAPE	RMSPE	MAPE	RMSPE
1	Pure SVR	3.92%	5.45%	4.05%	5.07%
	SL-SVR	3.35%	4.49%	3.96%	5.11%
	FL-SVR	2.85%	3.54%	3.77%	4.65%
	CL-SVR	3.47%	4.08%	3.78%	4.86%
	ML-SVR	3.36%	4.18%	3.34%	4.07%
	WL-SVR	2.86%	3.56%	3.53%	4.83%
	En-SVR	**2.11%**	**2.73%**	**2.27%**	**2.65%**
2	Pure ELM	3.94%	5.49%	3.95%	5.04%
	P-SL-ELM	3.59%	4.60%	3.69%	4.90%
	P-FL-ELM	2.91%	3.57%	3.73%	4.75%
	P-CL-ELM	3.61%	3.99%	3.71%	4.73%
	P-ML-ELM	3.52%	4.02%	3.47%	4.11%
	P-WL-ELM	2.78%	3.58%	3.39%	4.63%
	P-En-ELM	**2.20%**	**2.86%**	**2.32%**	**2.78%**
3	Pure SVR	3.92%	5.45%	4.05%	5.07%
	P-SL-SVR	3.64%	4.65%	3.93%	5.07%
	P-FL-SVR	3.06%	3.87%	3.83%	4.99%
	P-CL-SVR	3.44%	3.95%	3.76%	4.64%
	P-ML-SVR	3.48%	4.08%	3.38%	4.05%
	P-WL-SVR	3.11%	3.51%	3.84%	4.73%
	P-En-SVR	**2.21%**	**2.89%**	**2.35%**	**2.81%**
Proposed model	**En-ELM**	**2.09%**	**2.69%**	**2.22%**	**2.58%**

Figure 4 Forecasting Error Values in Chi Jie Lu et al. Research [13]

	BU	AHP	PHA	FP	NND	OPT
TOTAL	1.090	**0.974**	**0.974**	**0.974**	**0.974**	1.088
M1	1.745	1.520	1.549	1.092	**1.002**	1.249
M2	1.759	1.062	1.271	1.174	**1.013**	1.432
M3	1.158	1.361	1.355	0.963	**0.892**	1.170
M4	1.475	1.612	1.694	1.128	**1.038**	1.465
M5	0.999	1.075	1.063	1.181	**0.873**	1.132
M6	1.352	1.486	1.520	1.821	**0.769**	1.621
M7	1.044	1.771	1.678	1.174	**0.637**	1.087
M8	1.029	1.042	1.041	1.323	**0.892**	1.053
M9	1.070	1.272	1.244	0.997	**0.893**	0.975
M10	**1.045**	1.573	1.564	1.620	1.051	1.340
M11	1.225	1.452	1.437	1.382	**0.840**	1.131
M12	1.430	1.468	1.411	1.163	**0.821**	1.342
M13	**1.002**	1.872	1.715	1.496	1.090	1.682
M14	1.041	1.162	1.164	1.391	**0.820**	1.121
M15	1.348	1.533	1.553	1.893	**0.863**	1.185
M16	1.095	1.055	1.174	1.831	**0.844**	1.457
M17	1.292	1.806	1.759	1.706	**1.122**	1.131
M18	1.263	1.824	1.826	1.393	**1.047**	1.299
M19	1.436	1.730	1.789	1.218	**0.882**	1.280
M20	1.240	1.310	1.331	1.008	**0.987**	1.016
M21	1.326	1.317	1.343	1.176	**0.802**	1.106
M22	1.431	1.108	1.078	1.316	**0.924**	1.380
M23	1.164	1.353	1.309	1.419	**0.830**	1.153
M24	1.284	1.705	1.740	1.532	**1.165**	1.232
Average Meter	1.261	1.436	1.442	1.350	**0.921**	1.252

Figure 5 Forecasting Error Values in the Reseach of Paolo Mancuso et al. [18]

Store	Data Usage Rate	Bayesian	Boosted	Decision	Stepwise
A	40%	91,2%	89,9%	90,9%	91,8%
	50%	91,2%	89,5%	90,4%	
	60%	91,0%	89,6%	89,8%	
	70%	91,2%	89,3%	90,6%	
	80%	91,4%	89,3%	91,2%	
	90%	91,5%	90,2%	91,4%	
	100%	91,7%	89,2%	91,0%	
B	40%	87,2%	86,2%	87,2%	88,9%
	50%	87,0%	86,3%	87,2%	
	60%	87,1%	86,1%	86,8%	
	70%	87,3%	86,3%	86,9%	
	80%	87,3%	86,7%	86,9%	
	90%	87,4%	86,7%	86,8%	
	100%	87,6%	87,0%	86,5%	
C	40%	84,6%	83,1%	83,3%	
	50%	84,5%	83,7%	85,0%	
	60%	84,7%	84,6%	83,9%	
	70%	84,5%	83,8%	84,4%	86,0%
	80%	84,7%	83,8%	83,6%	
	90%	84,4%	84,2%	84,8%	
	100%	84,4%	82,9%	84,4%	
D	40%	83,8%	83,3%	84,8%	85,7%
	50%	84,5%	84,7%	84,2%	
	60%	85,1%	83,1%	85,5%	
	70%	85,0%	83,0%	84,9%	
	80%	85,1%	82,7%	84,9%	
	90%	85,5%	83,5%	85,1%	
	100%	85,8%	82,7%	84,2%	
E	40%	85,2%	86,3%	86,3%	84,6%
	50%	84,1%	86,2%	86,0%	
	60%	84,5%	86,1%	85,0%	
	70%	84,8%	86,2%	84,0%	
	80%	84,7%	87,2%	84,5%	
	90%	84,8%	86,8%	84,2%	
	100%	85,0%	87,3%	85,5%	

Figure 6 Forecasting Accuracy Values in Takashi Tanizaki's Research [24]

Table 1 Comparison of Variables Used in Demand Forecasting with Machine Learning

Writer	Variable
Takashi Tanizaki, Tomohiro Hoshino [24]	Number of sales days in a week and month, Weather, Event
Jakob Huber, Heiner S [10]	Calendric Special Days
FL Chen [7]	Competitor Sales, Price, Weather Data
Shuojiang Xu, Hing Kai Chan [27]	Disease Information from Search Engine
Shaohui Ma, Robert Fildes[15]	Promotional Activities, Prices, Displays

Base forecaster	Horizon								
	h=1		h=4		h=7		h=1-7		
	sMAPE	AvgRelMAE	sMAPE	AvgRelMAE	sMAPE	AvgRelMAE	sMAPE	AvgRelMAE	MPE
ETS	19.305	1.000	20.105	1.000	21.152	1.000	20.219	1.000	2.163
ADL-1	16.842	0.885	17.691	0.871	18.743	0.867	17.756	0.869	-0.339
ADL-3	16.999	0.893	17.929	0.883	19.053	0.886	17.957	0.882	**0.247**
ARX-1	17.246	0.907	18.059	0.904	18.996	0.894	18.190	0.902	1.045
ARX-3	18.101	0.952	18.924	0.945	19.900	0.942	19.055	0.947	1.154
ELM-1	17.959	0.932	19.280	0.956	20.629	0.984	19.448	0.970	**0.254**
ELM-3	19.744	1.048	20.679	1.043	21.654	1.038	20.739	1.041	1.602
SVM-1	17.175	0.915	17.950	0.909	18.833	0.894	18.058	0.907	1.283
SVM-3	17.531	0.925	18.380	0.922	19.347	0.920	18.467	0.923	1.693
GBRT-3	16.372	0.846	17.353	0.853	18.601	0.861	17.379	0.847	-1.653
GBRT-7	**16.201**	**0.844**	**17.137**	**0.842**	18.597	0.870	**17.301**	**0.847**	-1.558
ADLP-3	16.788	0.869	17.815	0.880	18.902	0.879	17.805	0.872	-1.927
ADLP-7	16.673	0.863	17.608	0.868	18.868	0.881	17.692	0.867	-1.514
RF-3	16.454	0.848	17.351	0.846	**18.580**	**0.853**	17.400	0.843	-1.328
RF-7	**16.318**	**0.836**	**17.186**	**0.840**	**18.554**	**0.856**	**17.293**	**0.837**	-0.798
ELMP-3	16.683	0.866	17.708	0.873	18.855	0.877	17.725	0.867	-1.570
ELMP-7	16.525	0.856	17.464	0.861	18.856	0.879	17.581	0.860	-0.700

Figure 7 Forecasting Error Values in Shaohui Ma's Research [15]

Table 2 Forecasting Error Values in Shuojiang Xu's Research [27]

Model	RSME	MAPE (%)
ARIMA	1655.91	14.99
ANN1	2295.70	18.74
ANN2	1708.82	15.05
SVM1	1800.85	16.07
SVM2	623.70	5.80

4. Conclusion

Different product characteristics have different approaches to producing accurate forecasting results. Approaches can differ in data processing, variable selection, and machine learning forecasting model selection. A reliable forecaster must determine the product's characteristics to be forecasted and then select the appropriate model and data processing method. The choice of forecasting model and method is also related to the error rate that can be accepted by the party doing forecasting, the higher the desired accuracy value, the company must constantly update the model and method to maintain the demand forecasting accuracy value. Based on the journal used as a reference, the value of forecasting accuracy with machine learning can reach above 90%.

The machine learning model most often used in previous studies is the Artificial Neural Network. Previous studies' models that produce high accuracy include Artificial Neural Networks, Support Vector Machines, and Decision Trees. The decision tree model produces high forecasting accuracy values at low forecasting time frames, such as daily and weekly demand forecasting. Modification of the demand forecasting method with machine learning can improve forecasting accuracy. Modifications to machine learning methods can be in the form of data processing and data grouping. Selecting the right variable can also improve the accuracy of demand forecasting results. The variables most often used in forecasting demand with machine learning are special events and demand history.

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