A Hybrid Artificial Neural Network and Logistics Regression Model for Fashion Sales Strategies Prediction

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Abstract

Sales prediction for fashion product is known to be very difficult, as we know the fashion demand is highly volatile with ever-changing customer's tastes and the product life cycle tends to be short. The purpose of this study is to predict the right strategy, between pre-order or vice versa using the deep learning function of Artificial Intelligence (AI). This research was conducted by combining AI using Artificial Neural Networks (ANN) with statistical methods using Logistics Regression (LR). The LR model was adopted as a pre-selection of input factors for the ANN prediction model (ANN-Logit). We also calculated the probability of each case using the logistic function then added as a new input variable for the ANN model (ANN-Plogit). The comparison was made to compare each model's performance. There is no significant difference between the outputs of each model. All models are considered good in predictions with fitness values above 0.85 and MSE tends to be small, but the hybrid ANN-Plogit provides slightly better than others with the highest fitness value of 0.995 and the lowest error (MSE) for 0.0012 with 98.6% prediction accuracy. This shows that the more input variables used as predictors, the better the fitness model. The models developed in this study may assist the firm in choosing the right strategy for upcoming product.

Keywords
Fashion demands, artificial neural network, logistics regression, pre-order strategy

1. Introduction
Fashion sector in Indonesia is the most desirable for online shopping. Based on data collected by the Indonesia Statistics Agency in 2019, the fashion sector was able to dominate 33% of the digital marketthe high demand coupled with its characteristics make it even more difficult to predict accurately. One of the factors is the fashion life cycle tends to be short, so the prediction of demand for a product needs to be precise as not causing deadstock when the selling season ends (Nenni et al, 2013). Furthermore, the selection of the right prediction method is very critical for fashion, choosing the right positioning strategy is important to avoid inaccuracies in demand prediction.

Several studies from the last decades discuss the change phenomenon in positioning strategy from the commonly used strategy, Make to Stock (MTS) into the rarely used strategy, Make to Order (MTO) (Ray et al, 2004; Garmdare et al, 2018; Sayid et al, 2018). The concept of MTS is that the presence of inventory items is used to keep the inventory levels to avoid stockout and lost sales, maintain a higher level of service by reducing the delivery times. (Shao et al, 2012; Zhang et al, 2013; Rafiei et al, 2013; and Xiong et al, 2020). Otherwise, MTO strategy starts production only after receiving the order so there is no inventory for the finished product. Therefore, longer delivery times are quoted to consumers (Xiong et al, 2020; Gupta et al, 2004 and Ebadian et al, 2008). The application of make to order is often associated with a unique and exclusive goods, such as a suit that is specially designed by talented designer as customer request, or a computer designed with special specifications based on the needs. However, today's business developments have shifted the about concept of MTO. This strategy has been successfully applied to such a mass production product in the market. Without a special uniqueness of a product, it has successfully sold with a pre-order system (we know as make to order strategy). For example, from this research object, a shoe variant with the market price for $50 selling at a retailer, will be priced around $30 with a 40-days number of waiting time, and $20 for a 60-days waiting. The main reason why the company adopts this strategy is the greater cash flow, which the working capital is obtained from customer payments in advance. The production process is carried out as soon as the payment made and will be completed within the quoted lead time so will be there no inventory costs. Some firms are focusing

on capitalizing of fashion trend that allows greater product variety and flexibility without worrying about deadstock after the sales season ends by implementing MTO strategy. To be able implement this strategy successfully, there is a cost that companies need to pay for the willingness to wait from customers, by offering a lower price than the market does (Ray et al, 2004).

Usually, the pre-order strategy is applied to special products with seasonal sales, such as Independence Day, holiday or as a result of collaboration with certain public figures. Meanwhile, non-pre-order products (we say it as MTS production) are applied to basic products with demand patterns tend to be stable and not affected by trends or seasonality. However, in some cases, pre-order products are also offered with a non-PO strategy after the pre-order period is over and still demanding. This phenomenon explains that the threshold for determining PO and Non-PO products is not clearly yet. As the successful implementation of pre-orders in the previous sales period, companies tend to do the same for upcoming products. therefore, it is possible that there are certain characteristics of a product as a key point to be successfully sold with PO.

This study was conducted to predict whether a product is worth to sell with a pre-order strategy or vice versa. Prediction will be carried out using ANNs as a complex computational model inspired by the human nervous system, which are capable of machine learning and pattern recognition. Furthermore, predictions with statistical methods will also be considered in this study for interpretations are easier to understand. Logistics Regression is one of statistical prediction tools that is suitable for the type of data in this study. The output studied is in the form of categories between pre-order and non-pre-order (1/0). The combining of these two models aims to adopt the concept of parsimony by selecting variables which can minimize the MSE (Seasholtz et al, 1993) and comparisons are made for each model developed, both the ANN itself and the combined model

1.1 Research Objectives

The first objective of this study is to predict the sales strategy using hybrid artificial neural network and logistics regression for sales of upcoming fashion product. The second is to compare the developed model with the existing model regarding the fitness of the model, error minimization and prediction accuracy. One of the contributions made by this research among others is this study examines the hybrid model of ANN and Logit in the fashion area. Which both models of LR and ANN are known that widely used in health and medical sciences (Hassanipour et al, 2019).

2. Literature Review

Similar prediciton studies have been carried out using neural network with the output in the form of categorical data before. Such as the studies carried out by Ayer, et al. (2010), Bourdès, et al. (2010), Shin, et al. (2012), Pergialiotis, et al. (2018), Nafouanti, et al. (2021) and Imperiale, et al. (2020) comparing the performance of both ANN with LR in prediction for categorical data. In addition, there are research by Yim and Mirchell (2003) combined the AI and statistical method to predict the corporate failure in Australia. Also, Schafer, et al. (2010) has combined between the LR and ANN to predict the broken of railroads construction. In the other hand, Fashion predictions using ANN have also been widely used, such as Cakravastia, et al. (2019) has done the demand prediction considering the variance of fashion product as the output, also the study by Chan and Chau (2019) formulated for both summer and winter fashion products.

From the comparison studies, some of results showed that ANN model has better prediction accuracy than LR. In general, ANN has a stronger predictor of LR because the interaction between variables does not affect the model. Otherwise, in order to study the causal relationship between variables, LR can be a right choice (Hassanipour et al, 2019). Also, the study of Predicting in-hospital mortality after primary liver cancer surgery showed that the ANN model in the study was more accurate with higher overall performance indices compared than the LR model (Shin et al, 2012).

On the contrary, Schafer, et al (2010) found the disadvantages of ANNs when compared to logistic regression models. ANNs frequently have difficulty analyzing systems that have a high number of parameters due to the large amount of time taken to learn the system as well as possibly over-fitting the model during the initial learning phase. So, using hybrid ANN and LR with output failure and non-failure found that only these 23 of the 28 input factors included in this analysis were considered to be factors that influenced the occurrence of a service failure of their study. After comparison, it shown that the Plogit-ANN hybrid model was found to be the most accurate model with a 67.9% correct classification rate, it has explained that the Plogit-ANN hybrid model performed better than any other developed

classification model including the logistic regression technique and the Logit-ANN hybrid model preformed worse than the stand-alone ANN. Here Table 1 is the comparison of some research in categorical prediction using ANN and logistics regression.

Table 1. Literature review

Researchs	Topics	Area	Methods	Scope	
				Compare	Combine
Yim and Mirchell (2003)	Predicting Corporates Failure	Economic / Finance	ANN, LR, DA	v	v
Green, et al. (2006)	Predicting the Acute Coronary Syndrome in Emergency Room	Health and Medical Science	ANN, LR	v	-
Ayer, et al. (2010)	Predicting the risk of breast cancer	Health and Medical Science	ANN, LR	v	-
Bourdès, et al. (2010)	Prediction of Breast Cancer Patient Outcomes	Health and Medical Science	ANN, LR	v	v
Schafer, et al. (2010)	Prediction of Broken Rails.	Railroads Construction	ANN, LR	v	v
Pergialiotis, et al. (2018)	Prediction of endometrial cancer in postmenopausal women	Health and Medical Science	ANN, LR, CART	v	-
Hassanipour, et al. (2019)	Prediction of outcomes in trauma patients	Health and Medical Science	ANN, LR	v	-
Nafouanti, et al. (2021)	Prediction on the fluoride contamination in groundwater	Chemical	ANN, LR, RF	v	-
This study	Prediction the appropriate strategy of new fashion product.	Fashion	ANN, LR	v	v

3. Methods

The traditional statistical methods, Artificial intelligence (AI) methods and a new hybrid method will be carried out in this study.

3.1 Artificial Neural Network

ANN is a model intended to simulate biological 'neurons' behavior of a human brain that could learn from the past experiences to provide outcomes for new data. It is suitable for classification and prediction tasks in some practical situations because of its capability of learning from a certain dataset (Pergialiotis et al, 2018). The Multilayer Perceptron (MLP) neural network used in this study, composed of input, hidden, and output layers. The input layers were formed of 11 neurons or less, which the number of predictor variables depends on which model used. In the output layer, the activation function depends on the prediction of the model. For this analysis, the sigmoid activation is applied in the output layer. Each layer consists of a fundamental element named neurons, which have thresholds and an activation function that are important to the training process (Nafouanti et al, 2021). As mentioned by Nenni, et al (2013) Artificial neural network (ANN) is probably the most used techniques for sales forecasting, especially for short-term forecasts where the main issue is to give more importance to the latest known sales.

ANN methodology used in this study as follows: (1) provide sets data of input and output variables information for ANN training, (2) normalize the input and output data to prevent larger numbers from overriding smaller ones (3) training and continuously testing normalized data to get the best ANN architecture, and (4) compare each model output (5) predict number of hypothetical data using selected ANN model to gain insights as recommendation.

3.2 Logistics Regression

Logistic regression (LR) is an efficient algorithm that is fast in dataset training and efficiently used to analyze binary classification (Nafouanti et al, 2021). It is used to describe data and to explain the relationship between one or more

nominal, ordinal, interval, or ratio-level of independent variables with a dependent variable in the form of nonmetric (binary). Mathematically, LR is based on probability, odds ratio, and logarithm of odds. Odds ratio is defined as the ratio between the probability of an event occurred and the probability of an event not occurring (Kirişci et al, 2019). The significance of each variable is defined in terms of the statistical significance of the coefficient for the variable shown as p-values. The significance criterion that generally used when testing for the statistical significance of variables is p≤0.05 (Schafer et al, 2010).

As the research done by (Kirişci et al, 2019). Y is the estimated probability that the i-th item belongs to one that means an event occurred (Y=1) of the categories of the dependent variable.

$$Y_i = \frac{e^T}{1 - e^T}$$

Where T is defined as,

$$T = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

The concept of Logit is defined natural logarithm of odds ratio,

$$\ln\left(\frac{Y_i}{1 - Y_i}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

4. Model Development

The ANN prediction model is used to predict the strategy of an Indonesian fashion brand especially in shoes in who sells their product through online marketing platforms. Their product sold with both of strategies, non-PO and PO strategies. The 11 input variables were selected based on product design factors such as color, size, materials etc, also sales factors such as product prices and discounts as shown on Table 2. ANN model is proposed to predict the right strategy based on each character of product. Here are the variables information that used in this study.

Table 2. Variable information

No	Variables	Type	Scale	Reference
1	e-Commerce Platform	Input	Categorical	Venkatesh and Davis (2000); Min and Galle (2003)
2	Availability Platform	Input	Categorical	O'Cass and Fenech (2003); Shang dkk, (2005)
3	Variant Product	Input	Categorical	Bodenstab (2016)
4	Style	Input	Categorical	Drew dan Sinclair (2014)
5	Outsole Material	Input	Categorical	
6	Insole Material	Input	Categorical	
7	Upper Material	Input	Categorical	
8	Discount	Input	Numeric	Permatasari (2019) and Apriana (2020)
9	Price	Input	Numeric	
10	Status	Output	Categorical	

All the Input and output variables will be normalized using min-max normalization to scale the input and output variables into the range of value [0,1]. This is done to prevent inhibition of the learning process caused by the larger number of overriding the smaller ones and premature saturation of the hidden neurons (Chan and Chau, 2019). In this study, as follow.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

The eleven input variables will be training using ANN prediction tool in the next session. The use of logistics regression is to explain the significance between dependent binary variable and each independent variable. Only independent variables are considered important in predicting the outcome that will be included on LR Models. Here is the SPSS output using the enter selection methods to determine which parameters are significant for prediction. From the first iteration can be chosen the most significant variables by criterion $p \leq 0.05$.

Out of 11 input variables, only 6 variables are significant for prediction that will be used as input variables of ANN for the developed ANN-Logit model shown as Table 3. The selected variables including product variants, style of product, color, upper material, unit price and the discount.

Table 3. The output of LR model using enter selection method

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Platform	-17.431	1740.871	.000	1	.992	.000	.000	.
	availability	22.866	1740.871	.000	1	.990	8521445882	.000	.
	varian	-6.970	1.286	29.355	1	.000	.001	.000	.012
	style	5.004	.839	35.582	1	.000	149.068	28.792	771.785
	size	-1.007	1.325	.577	1	.447	.365	.027	4.906
	color	-7.907	1.365	33.570	1	.000	.000	.000	.005
	upper_material	-1.777	.877	4.103	1	.043	.169	.030	.944
	Insole_material	.195	.995	.039	1	.844	1.216	.173	8.544
	outsole_material	-.250	.980	.065	1	.798	.779	.114	5.313
	price	-8.107	1.161	48.718	1	.000	.000	.000	.003
	Discount	-4.733	2.334	4.110	1	.043	.009	.000	.855
	Constant	-7.270	870.437	.000	1	.993	.001		

From the output above, the logistics function of each option (6 selected variables and 11 variables) is:

$$P_{11(y=1)} = \frac{e^{-7.28-17.34Pl+22.86A-6.97V+5.004S-1.007Si-7.907C-1.77U+0.23I-0.502O-8.107P-4.73D}}{1+e^{-7.28-17.34Pl+22.86A-6.97V+5.004S-1.007Si-7.907C-1.77U+0.23I-0.502O-8.107P-4.73D}}$$

Only the significant variables considered to construct this probability function as follows:

$$P_{6(y=1)} = \frac{e^{-7.283-6.97V+5.004S-7.907C-1.777U-8.107P-4.733D}}{1+e^{-7.283-6.97V+5.004S-7.907C-1.777U-8.107P-4.733D}}$$

Where, Pl as platform of e-Commerce, A as availability of stock each platform, V as variant of products, S as style of products, Si as size of products, C as color of products, U as the upper material, I as the insole material, O as the outsole material of products, P as price per unit product, and D as discount earned. Then the probability function will be added into the ANN as a new input for the developed ANN-Plogit model

4.1 Artificial Neural Network Classification Model

Designing parameters of the ANN model such as number of hidden layer and number of neurons need to be determined before constructing the appropriate ANN model. Firstly, we compute the range of the number of neurons in the hidden layer to be investigated then the optimal number of neurons in the hidden layers could be determined after evaluating the fitness of models (Chan and Chau, 2019):

$$2 \times \sqrt{N_i} + N_o \leq N_h \leq 2 \times N_i + 1$$

N_i as number of input variable; N_h as number of Neuron, and N_o as number of output variable. Using the MATLAB toolbox for neural networks (nntool) with feed-forward backpropagation and Levenberg-Marquardt as a training function, we train the model. Select the Logistic Sigmoid (logsig) as the activation function of hidden layer and output layer. The training only takes 80% of the input data and the rest is used for model testing. The optimal ANN architecture will be found after many trials to gain the best performance in terms of the lowest MSE. Here is the ANN design of each developed model.

Table 4. the comparison of developed ANN architecture

Architecture	ANN	ANN-Logit	ANN-Plogit	
Input	11	6	7	12
Output	1	1	1	1
Hidden Layer	1	1	1	1
Neuron	$8 \leq N_h \leq 23$	$6 \leq N_h \leq 13$	$6 \leq N_h \leq 15$	$8 \leq N_h \leq 25$

Replications for each number of neurons was carried out 3 times of training. The ANN architecture that has the best performance is chosen as the strategy prediction ANN model for fashion products. Figure 1 shows the architecture of ANN in this study.

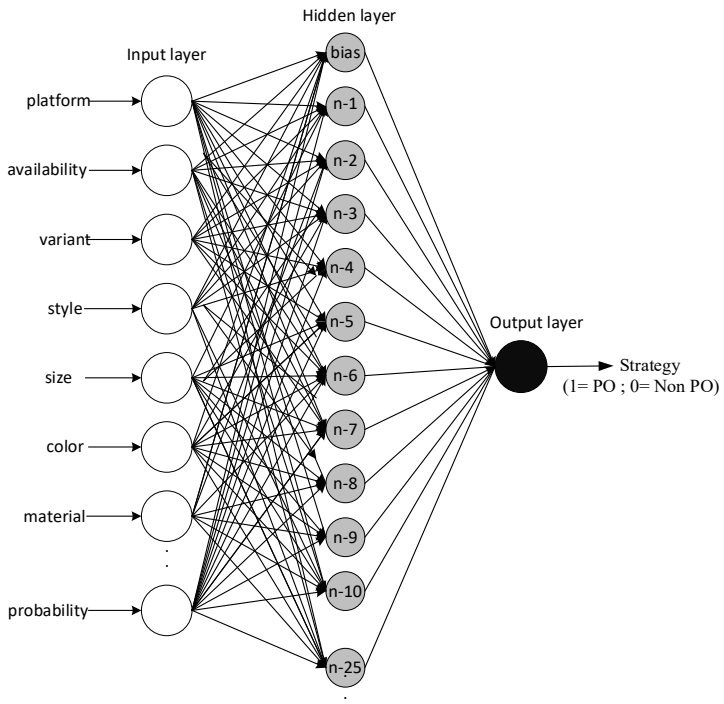

Figure 1. ANN architecture

5. Results and Discussion

Using 1312 data train as the learning function of the ANN model, the output performance for prediction is shown in Figure 2 for the ANN-Plogit architecture with 12 input variables and Figure 3 is the ANN-Plogit architecture with 7 input variables. The results of ANN-Plogit Model in Figure 1 show a promising result. Based on each replication of number of neurons in the mentioned range, a network with 23 hidden neurons results as the best architecture for predicting the optimal strategy with an MSE value of 0.00017 and a fitness model of 0.9985.

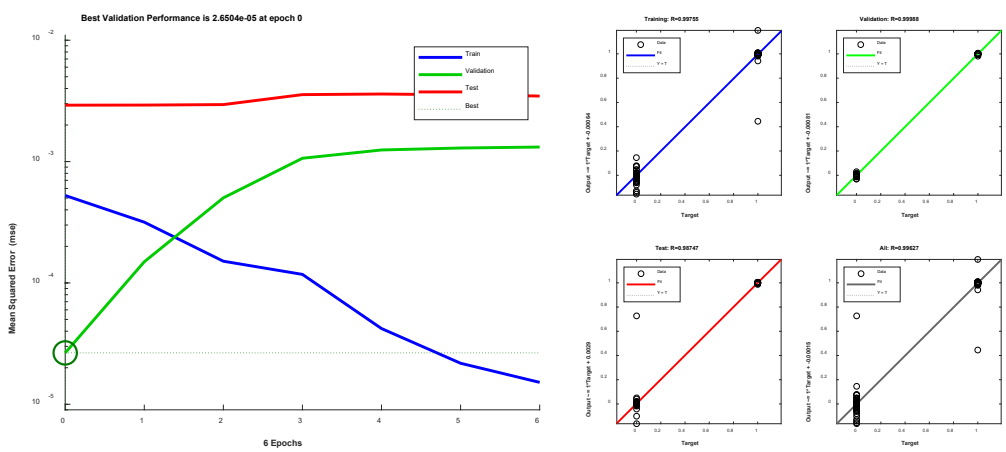

Figure 2. ANN performance output 12 input variables

On the other hand, eliminating the not significant variables takes as account to build the prediction namely ANN-Plogit Model. Only seven variables by considering the selection of significant variables and adding the probability

function as a new input for the model prediction. The best replication was obtained with a network of 7 neurons with an MSE value close to 0 which is 0.0000013 and an MSE close to 1 which is 0.9994 shown as Figure 3.

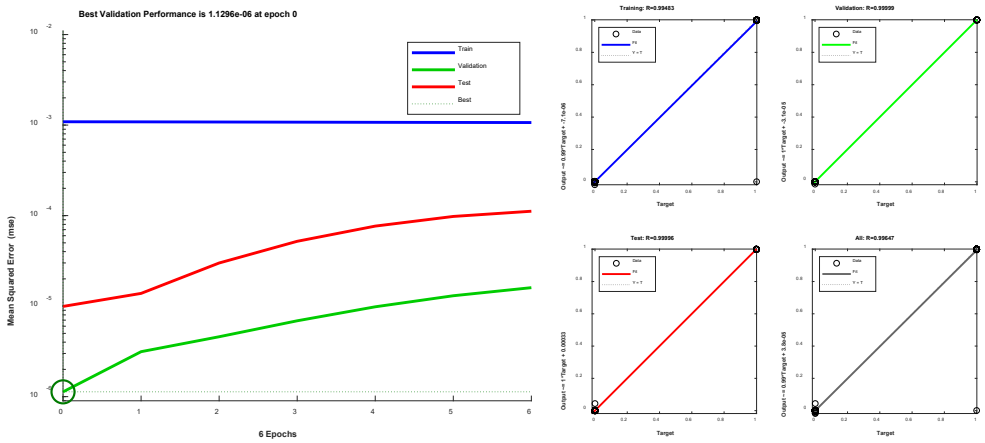

Figure 3. ANN performance output 7 input variables

Testing the model is also carried out with 327 data-test using the ANN architecture selected from the previous train function, namely 12 input variables with 23 neurons and 7 input variables with 7 neurons. It shows the prediction results are mostly in accordance with the real dataset, the comparison graph can be seen in Figure 4.

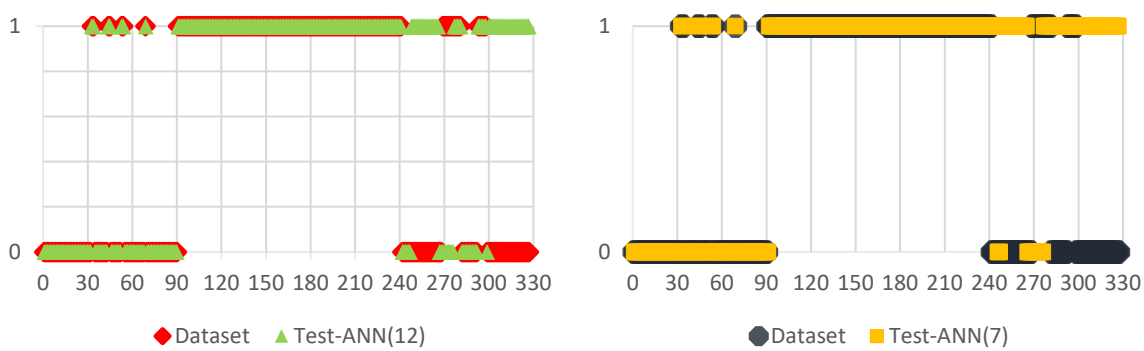

Figure 4. Prediction pattern of 12 and 7 input variables

Then we do the comparison of each model's output based on each developed model of ANN from the architecture on Table 4, as shown on table 5.

Table 5. The comparison of the ANN Models

Model	Input Variables	No of Neuron	MSE	Fitness (R)	% Accuracy
ANN	11	8	0.004404	0.9903	97.8%
		23	0.009131	0.9943	98.4%
ANN-Logit	6	6	0.023914	0.9574	98.6%
		13	0.01118	0.9606	97.8%
ANN-Plogit	7	6	0.00637	0.9737	97.9%
		14	0.99918	0.00017	98.5%
	12	9	0.00051	0.9947	98.6%
		23	0.00002	0.9998	98.4%

Based on the comparison of each model above, the developed ANN-Plogit Model with 12 inputs provides the lowest mean squared error for 0.0012 and the fitness value of 0.995 close to the value of 1. According to research conducted by (Schafer et al, 2010) they found that The Plogit-ANN hybrid model was found to be the best model among other developed ANN.

The differences shown by each model in this study were not significantly different. all models are considered good in prediction with fitness values above 0.85 and MSE tends to be small. This shows that the more input variables used as predictors, the better the fitness (R) value of the ANN model. It means the significant relationship between a dependent variable and independent variables no need to be explained by using ANN. Shows that the interaction between variables does not affect the ANN performance (Hassanipour et al, 2019)]. So, if there are implicit interactions and complex relationships in the data, the use of ANNs is particularly useful (Ayer et al, 2010).

5.1 Prediction Result

Prediction is done using ±300 hypothetical datasets for the ANN model that has been selected in the previous section, the aim is to get recommendations for product characteristics that are suitable for upcoming product sales in the future.

Table 6. Prediction using hypothetical datasets

Platform	**Product Specifications**				**Material of the Product**			**Price**
e-*Commerce*	***Style***	**Variant**	**Size**	**Color**	**Upper**	**Insole**	**Outsole**	
P1, P2 and P3	Sn	BS	40,42,43	Bl*	BM	AM +LF	Ph	IDR299,000
			40, 43	Bl*	FL	BM	TR	
		Gr	41,42,43, 44	DB*, Bl*	Tw	F	TR	IDR 599,000
	LCB	SL	40,41,43, 44	Bl*, Br*	PUL	EA	EFF + R	IDR 215,460 - 264,060
		Nt	40, 41, 43, 45	Bl*	PUL	E	TR	IDR 299,000
		Tb	39, 40, 42, 43, 45	Bl*, Br*, DB*	PUL	Pf	R	IDR 525,000

*) Bl: black, DB: dark brown, Br: brown

From the prediction results in the Table 6 above, some insights that can be obtained are: product X is sold online through 5 digital platforms. However, in practice not all platforms are considered reliable for purchasing pre-order products. 3 out of 5 selected as platforms for PO implementation. Based on the product style, it is found that the Sn style of product with its character that is considered 'timeless' is suitable for the PO strategy. In addition, products with LCB style that are known to be unique and special are also suitable for pre-order strategies. From 23 product variants that have been produced by brand X over the last two years, turns out that only five products matched the pre-order based on ANN's study. And the targeted consumers are generations of Y and Z, which is a young population dominated by men in the age between 17 and 30 years. The learning function of ANN read that not all sizes are the most desirable for the pre-order strategy, which only sizes 39 to 45 are the most ordered sizes when purchased for PO.

6. Conclusion

Four strategy classification models were developed to assist in the prediction of pre-order strategy selection towards the upcoming product of fashion. ANN as the tool basis for prediction model of an Indonesian fashion brand especially in shoes in who sells their product through e-Commerce. The objective of this study is to predict the right strategy, between pre-order or non-pre-order using the deep learning function of Artificial Intelligence. Combining the advanced prediction using ANN with statistical method using logistics regression carried out in this study. The LR model adopted as pre-selection stage of input factors for the ANN prediction model (ANN-Logit). Also calculate the probability of each case using logistics function of LR then added as an input variable for ANN prediction model (ANN-Plogit). The comparison is made to compare each model's performance. There is no significant difference between each model output. All models considered good in prediction with fitness values above 0.85 and MSE tends to be small, but the hybrid ANN-Plogit slightly better than others with the highest fitness value (R) of 0.995 and the lowest error (MSE) for 0.0012 with 98.6% accuracy of prediction. This shows that the more input variables used as predictors, the better the fitness model. As the results of LR model, there are six variables that significantly affect the

predictors: product variants, style of product, color, upper material, unit price and the discount. Let's take a price as example, it has negative relationship with predictors. Means that the cheaper the price, the more likely a pre-order strategy will be occurred. Based on the prediction results using hypothetical data, it obtained that not all data ranges for each factor are in accordance with the character of Pre-order sales. Such as product variants, 5 out of 23 variants were successfully sold by PO, and only certain product styles were most in demand for pre-order purchases. The models developed in this study may assist the firm in selecting the right strategy for upcoming product in the future with several inherent product characteristics.

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