Article-INFUS 2021 Special Issue

Machine Learning Sales Forecasting for Food Supplements in Pandemic Era

Funda Ahmetoğlu Taşdemir [1,*]

[1] Department of Industrial Engineering, Izmir University of Economics, Izmir (35330), Izmir Province, Turkey

[*] Correspondence: funda.tasdemir@izmirekonomi.edu.tr; Tel.: +90-0232-488-8261

Abstract: The Covid-19 pandemic has brought a lot of concerns about the operational and financial situation of businesses. Forecasting is crucial as it guides businesses through these critical points. Forecasting has become even more critical in the pandemic environment and therefore the necessity of using an accurate forecasting method has increased. Taking this into consideration, in this study, intelligent machine learning methods, namely; Grey Model (GM), Artificial Neural Network (ANN) and Support Vector Machine (SVM) are applied to make a short-term prediction of a food supplement, a product whose demand increased with the pandemic situation. Eighty-five percent of the historical data is used for training purposes and fifteen percent of the data is used for measuring accuracy. The accuracy of the models employed is improved with parameter optimization The accuracy performance indicator Mean Absolute Percentage Error (MAPE) showed that all methods give superior results when the historical data has an increasing sales trend. This study presents an important consideration for businesses and has a potential to be generalized for a business whose sales have an increasing trend not only because of the pandemic but also for any reason.

---

1. Introduction

Sales forecasting is essential for a company to make strategic decisions, especially to achieve better production planning, inventory control and financial estimation [1]. Sales forecasts especially form the basis for supply policies, therefore poor forecasting causes too much or too little stocks, directly affecting competitiveness and revenue [2]. Therefore, improving the accuracy of forecasts will provide better operational efficiency and financial savings. Taking this into consideration, many algorithms have been developed to take the advantages of more accurate forecasts [3].

In many decades, statistical models have been widely applied in conducting forecasting. Statistical models are effective and the study can be completed in a very short time even if the data set is large, but they may underperform with complex data pattern [4]. Machine learning methods, which have been used more recently, are more efficient and flexible than traditional statistical techniques for forecasting since they have a better processing power [5]. Tarallo et al. [6] made a comprehensive investigation for the machine learning techniques emphasizing their superiority to

traditional statistical techniques. Many forecasting studies were conducted to evaluate and compare statistical and machine learning methods, both within themselves and with each other.

Ansuj et al. [7] applied autoregressive integrated moving average (ARIMA) and ANN methods to forecast sales in a medium-sized enterprise and found more accurate results with ANN according to mean absolute error (MAE) measurement. Kotsialos et al. [8] compared Holt-Winter's method and ANN for sales forecasting of two German companies and found slightly better results with ANN. Tanaka [9] proposed a sales forecasting model with a knowledge-based database observing correlations for new-released and nonlinear sales trend products and results showed that their proposed model is superior to applied statistical methods; moving average (MA) and exponential smoothing (ES) according to MAPE indicator. Kandananond [10] applied ANN, SVM and ARIMA to predict demand for six different consumer products and found out that for each product, SVM performs better than ANN and ARIMA according to MAPE measurement. Choi et al. [11] examined ANN, ANN+GM hybrid model and GM to forecast color trend of a fashionable product by employing real sales data and found that the latter gave best MAPE value. Yu et al. [12] used SVM for newspaper/magazine sales forecasting and their experiment showed SVM is very successful in this kind of task. Du et al. [13] used SVM and ANN for forecasting demand of perishable farm products and results show that SVM outperformed ANN. Kitapçı et al. [14] forecasted automobile sales with linear regression (LR) and ANN; the mean square error (MSE) and MAPE measurements showed ANN was more successful than LR. Xia and Wong [15] established a seasonal discrete GM for one-step-ahead forecasting sales of fashion products using real sales data of three different retailers and compared their model with ANN, autoregressive (AR), GM (1,1), Markov GM (1,1), Tseng's model and fuzzy grey regression model; and they found the lowest MSE and MAPE with their proposed model. Pillo et al. [16] applied SVM and the statistical methods; ES, Holt-Winter's ES (HWES) and ARIMA to forecast sales of a commodity in retail and they got the lowest MSE value from SVM, suggesting any sales manager to consider using the SVM method rather than conventional methods. Vhatkar and Dias [17] forecasted the sales of three different types of oral-care goods with ANN. They used mean absolute deviation (MAD), MSE and root mean square error (RMSE) performance measurements and concluded that ANN gave accurate results. Karmy and Maldonado [18] applied SVM for forecasting sales of duty free and travel retail industry. The MAPE indicator showed that SVM gave higher forecasting accuracy compared to ARIMA and Holt-Winter methods applied. Güven and Şimşir [19] used ANN and SVM for sales forecasting of different products in retail garment sector and according to MSE, both methods yielded good results, with ANN slightly more successful. Zhang et al. [20] forecasted the monthly sales of cigarettes by applying ARIMA, seasonal ARIMA, Winter's multiplicative model and their own model in which they take seasonal and trend factors into consideration. Their proposed model gave the lowest error percentage. Taşdemir and Şeker [21] applied GM (1,1), ANN and fuzzy time series to find one-step ahead forecast of a cleaning product and the APE measurement showed that all the models gave superior results.

Based on the literature review above, machine learning methods have been very successful in sales forecasting. Obviously, the Covid-19 pandemic has changed the sales tendencies of some products in a positive way and change in trends has disrupted the forecasting process. To minimize the effects of this change, the necessity of the reliable methods increased. Therefore, this study has aimed to make a short-term forecasting for the sales of a food supplement with three reliable machine learning methods, namely; GM, ANN and SVM. Although there are important studies in the

literature on sales forecasting with GM, not much research has been conducted on comparison of GM with ANN and SVM methods together. This study contributes to the literature with comparative application of these 3 models. In addition, all models have been improved by optimizing their parameters before the final comparison is made. The underlying challenge of the task was utilizing these methods with limited historical data and this is especially may not be a good option for ANN, however, this problem can be reduced to some extent by parameter optimization.

The remainder of this paper is structured as follows: Section 2 describes the methodology of the methods applied to make short-term forecasting and evaluation measurement used for the accuracy of these methods. Section 3 describes the application of the methods with optimized parameters in details and summarizes the outputs. Section 4 presents the conclusion for the whole study.

2. Methodology

2.1. Grey Theory

The grey system model is first proposed by Deng [22] and GM (1,1) is the simplest form of this model which is widely used for forecasting. GM (1,1) requires at least four observations and has high forecasting capability with small samples. In GM (1,1), an accumulated generation operation (AGO) is applied to construct differential equations to get the forecasted output from the system [23]. The GM (1,1) formulation is given in the following [24]:

Step 1: Consider an original series to be

$$x^{(0)} = x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n) \tag{1}$$

Step 2: A new sequence of $x^{(1)}$ series is obtained using the AGO.

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \dots, x^{(1)}(n)) \tag{2}$$

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \tag{3}$$

Step 3: A first-order differential equation is generated as follows:

$$(dx^{(1)}/dt) + \alpha z = v \tag{4}$$

$$z^{(1)}(k) = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k+1), \ k=1, 2, n-1 \tag{5}$$

α indicates a horizontal adjustment coefficient where $0 < \alpha < 1$. The selection criterion of α value is targeted to obtain the minimum forecasting error.

Step 4:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{u}{a}\right)e^{-ak} + \frac{u}{a} \tag{6}$$

$$\hat{\theta} = \begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{7}$$

$$B = \begin{bmatrix} -z^{(1)}(2) \ 1 \\ -z^{(1)}(3) \ 1 \\ \dots \quad \dots \\ -z^{(1)}(n) \ 1 \end{bmatrix} \tag{8}$$

$$Y = (x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n))^T \tag{9}$$

Step 5: Inverse AGO. Since the grey forecasting model is conducted by applying AGO data instead of the original data, IAGO can be employed to reverse the forecasting value as given in the following:

$$\hat{x}_0^{(0)} = (\hat{x}^{(1)}(k) - \hat{x}(k-1), k = 2,3,\dots,n \tag{10}$$

2.2. Artificial Neural Network

Artificial neural networks are computational models inspired by human brain and are used in forecasting problems [11]. A common ANN structure consists of some elements called input, hidden and output layers. Information is provided in the input layer, while the output layer produces the forecasting results. The hidden layer between those two layers establishes nonlinear relationships between inputs and outputs by adjusting weights which is called learning. The general structure of an ANN is given in Figure 1.
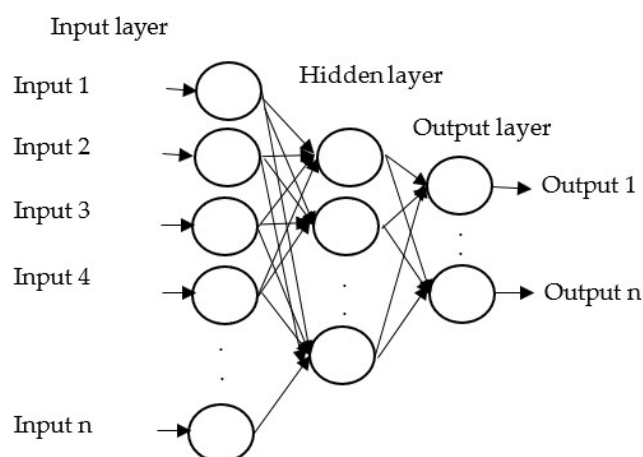

Figure 1. This Structure of ANN.

A special type of feedforward artificial neural network is multilayer perceptron (MLP) which is employed in this study. MLP consists of one input and one output layer and one or more hidden layers [25]. Mathematical calculation of MLP is given by following formula:

$$y = f_0\{\sum_{j=1}^{N} w_J f_H[\sum_{i=1}^{n} h_{ij} X_i + b_j] + b_0\} \tag{11}$$

where y is the output, x is the input vector, h_{ij} is the matrix of weight, b_j is the vector of bias, and f_H is the activation function of hidden layer, w_j is weight vector, b_0 is the bias scalar and f0 is activation function of output layer [26].

2.3. Support Vector Machine

The support vector machine was introduced by Vapnik [27] and it is one of the machine learning techniques used both for classification and regression. Although they were underestimated in the past, currently they can yield successful results which are comparable to those of ANNs and other intelligent methods [28]. SVM employs a linear function in a large space to test the forecasting regression. In SVM, forecasting is calculated by following formula:

$$f(x) = w^T x + b \tag{12}$$

where x is the input vector, b is bias and w is the weight vector [26].

An iterative algorithm for solving regression problems is called Sequential minimal optimization (SMO) and later improved by Shevade et al. [29] to solve regression problems which named SMOreg [30]. SMOreg is the function which will be the scope of this study.

2.4. Evaluation of Accuracy

One of the robust forecasting accuracy measurements is MAPE, which is proposed by Lewis [31]. According to Lewis, if the MAPE value is less than or equal to 10%, forecasting accuracy is evaluated high. The formulation for MAPE is given as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y(i)-\hat{y}(i)}{y(i)}\right| \times 100\% \tag{13}$$

where $y(i)$ is the actual value and $\hat{y}(i)$ is the predicted value of y for period i [32].

3. Application and Discussions

This study focuses on a food supplement whose sales have increased due to the pandemic and aims to provide an accurate forecast of the relevant product. The company never experienced any increase like this; especially an unprecedented one like amid pandemic, therefore the necessity of an accurate forecasting system has become much more critical than ever. To employ in the forecasting models, the original data was extracted from the company's data base and the data starts from March 2019, when the first covid case was seen in Turkey and ends in June 2020 which creates a total of 16 observations. Based on this data set, it is aimed to make a short-term forecast for the following 3 months. The GM (1,1), ANN and SVM methods mentioned in section 2 were used to perform the estimation and MAPE is used for evaluating the performance of these methods. By analyzing the results of these forecasting models, the company will decide whether to replace their legacy forecasting method since it is not satisfactory.

3.1. GM (1,1) Model Results

According to the formulations steps used in GM (1,1) given in section 2.1, the model is established using the original sales data of the food supplement.

Step 1: The original series belonging to related product are x(0) = {13280, 15045, …, 32870}.

Step 2: x(1) cumulative series are then calculated as x(1) = {13280, 28865, …, 366806}.

Step 3: The calculations showed that the best value for α is 0.16.

$$\begin{bmatrix} -26458 & 1 \\ -43215 & 1 \\ .. & ... \\ -361547 & 1 \end{bmatrix}, Y = \begin{bmatrix} 15045 \\ 17083 \\ ... \\ 32870 \end{bmatrix}, \hat{\theta} = (B^T B)^{-1} B^T Y = \begin{bmatrix} -0{,}0525 \\ 14353{,}1 \end{bmatrix}$$

Step 4: When we take $\hat{\theta}$ into consideration:

$$\hat{x}_0^{(1)}(k) = \left[x^{(0)}(1) - \frac{u}{a}\right](1 - e^a)e^{-a(k-1)}$$

The equation of GM (1,1) becomes:

$$\hat{x}_0^{(0)} = \left[13280 - \frac{143523{,}1}{-0{,}0525}\right](1 - e^{-0{,}0525})e^{-(-0{,}0525)(k-1)}, k = 2,3,\dots,n,n+1\dots$$

For next 3 months, GM (1,1) gives the following forecast values respectively: 34080, 35290, 37860.

3.2. MLP Results

The MLP model is established to forecast the 3 months ahead sales of food supplement product in Waikato Environment for Knowledge Analysis (WEKA) 3.8.5 software. The software is developed in Java by University of Waikato for machine learning studies. When the software is run, a screen with five different interfaces is displayed. The software also has a package manager where it is

possible to access various tools [28]. Forecast plugin is one of these tools which is installed to apply MLP and SMOreg models in this study (Figure 2).
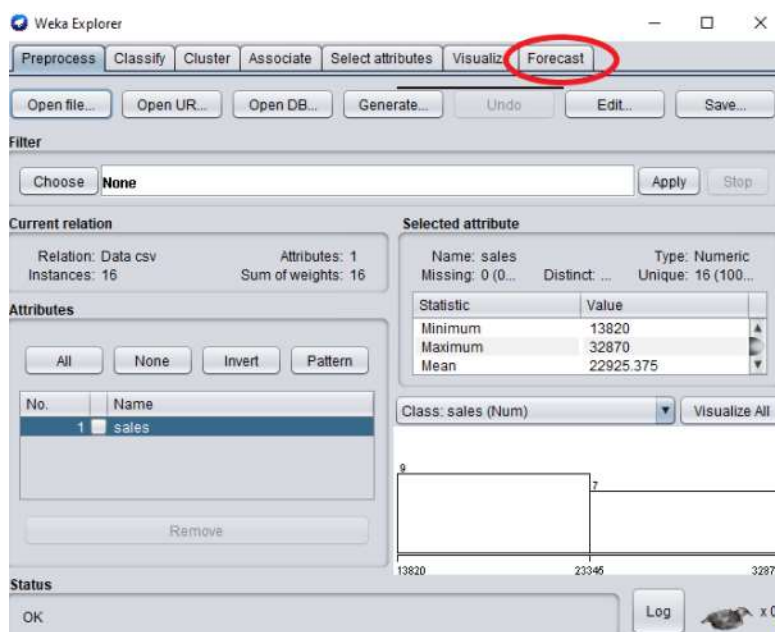

Figure 2. WEKA forecasting plug-in.

MLP models have some parameters to be optimized to reach best accuracy. These parameters are number of epochs (N), number of hidden layers, number of neurons, learning rate (L) and momentum (M). To train MLP, 85% of the data is used and several experiments have been applied to minimize MAPE. Table 1 shows the list of experiments and the obtained MAPE value accordingly. The first experiment shows the default parameters in WEKA. Firstly, the experiment was started with the first three trials of epoch number, and it was observed that the forecasting accuracy decreased due to the overfit of the model when the epoch number increased too much. When the number of epochs is reduced, the forecasting accuracy decreased again due to the inability of the model to learn enough. In the first, fourth and fifth experiments, other parameters were kept constant and the number of neurons was changed, and it was found that these changes decreased the forecasting accuracy again. The first and sixth experiments were examined to see how the number of hidden layers affected the prediction accuracy, and the results show that increasing the number of hidden layers from one to two significantly reduced the accuracy. In the transition from the sixth experiment to the seventh experiment, it is shown that the accuracy decreased when the number of neurons is decreased again while the number of hidden layers is still two. In the first, eighth and ninth experiments, the learning rate was changed and other parameters were kept constant. Accuracy increased when the learning rate was 0.2, unlike the default value. Finally, in the first, tenth and eleventh experiments, the momentum was changed and the other values were kept constant, and it was observed that the accuracy increased when the momentum value was 0.3. Based on the experiments conducted, the best value for MAPE is obtained with 500 epochs, 1 hidden layer, 10 neurons, 0.3 learning rate and 0.3 momentum as shown in Table 1. Figure 3 shows the actual sales between period 1 and 19 and the forecasted sales for period 17, 18 and 19 for the best set of parameters in MLP. The forecasted values are 34080, 35751 and 37132 respectively while the actual values are

34067, 35789 and 37893. It is revealed from Figure 3 that forecast values of the MLP are close to actual sales values.

Table 1. MLP parameters and corresponding MAPE values.

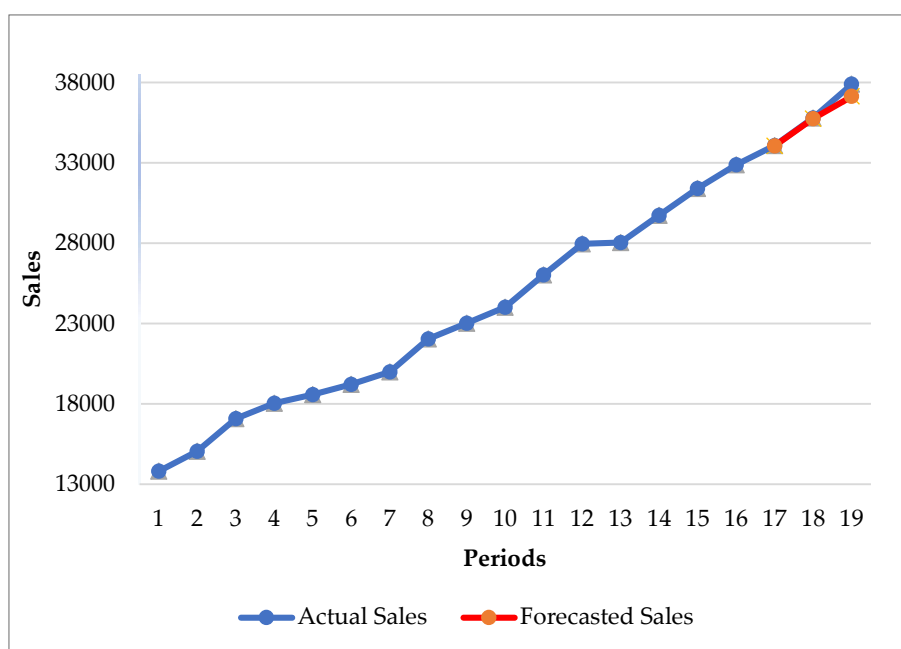| Experiment Number	Number of Epoch	Number of Hidden Layer	Number of Neurons	Learning Rate	Momentum	MAPE
1	500	1	10	0.3	0.2	0.86%
2	1000	1	10	0.3	0.2	1.43%
3	100	1	10	0.3	0.2	1.56%
4	500	1	5	0.3	0.2	1.41%
5	500	1	15	0.3	0.2	1.34%
6	500	2	10	0.3	0.2	4.01%
7	500	2	5	0.3	0.2	4.10%
8	500	1	10	0.4	0.2	1.47%
9	500	1	10	0.2	0.2	1.03%
10	500	1	10	0.3	0.3	0.72%
11	500	1	10	0.3	0.4	0.81%

Figure 3. Actual sales and forecasted sales of MLP.

3.3. SMOreg Results

The regression algorithm of SVM, which is called SMOreg is also established in WEKA environment. As in MLP, the same percentage in SMOreg is used for training purposes. In addition to this, SMOreg has also key parameters to be optimized, such as Kernel and complexity (C) parameters. Kernel function determines how to allocate data in the future space and C determines the flexibility of the line to separate different classes [33]. Kernel function can be selected in WEKA interface and the C parameter must be set by the user. The best setting of the parameters can only be found by experimentation [34]. The Kernels used in the experiments are Normalized Polynomial (Normalized Poly), Polynomial (Poly), Pearson VII (Puk) and Radial Basis Function (RBF). The C values applied are, 1 (the default parameter in WEKA), 2, 0.5 and 3. Table 2 shows 16 experiments performed with different Kernel and C parameters. The best MAPE value is obtained with Poly

Kernel and C = 3. Figure 4 shows the actual sales for periods 1-19 and the forecast results for period 17, 18 and 19 for the best experiment in SMOreg. SMOreg forecasted 34460, 35993 and 37854 respectively against actual values of 34067, 35789 and 37893. Figure 4 shows that SMOreg yields estimated values that approximate actual sales values.

Table 2. MLP parameters and corresponding MAPE values.

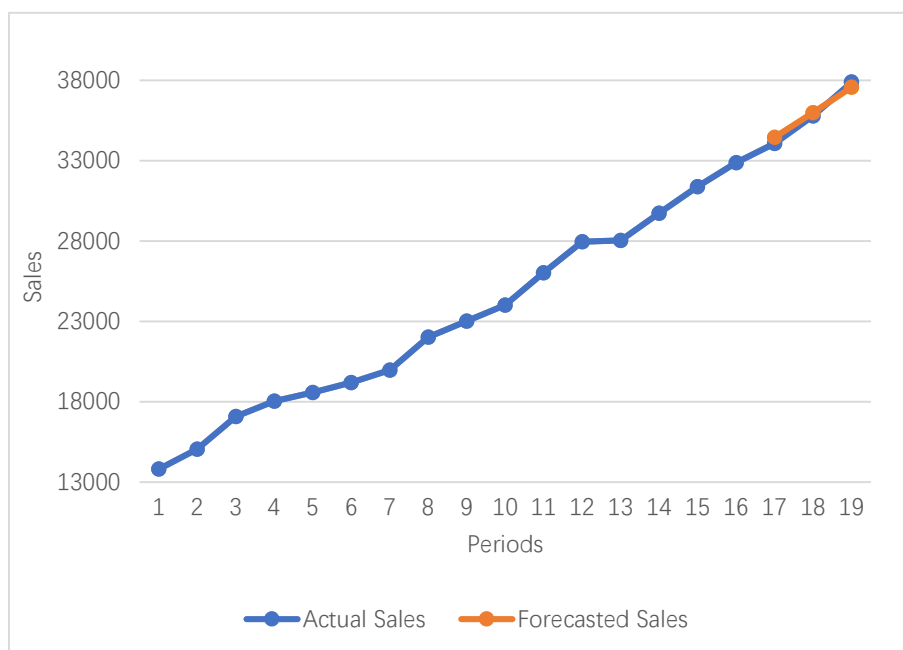| Experiment Number	Kernel Function	C	MAPE
1	Normalized Poly	1	26.78%
2	Poly	1	2.91%
3	Puk	1	28.78%
4	RBF	1	1.30%
5	Normalized Poly	2	19.12%
6	Poly	2	1.46%
7	Puk	2	28.78%
8	RBF	2	1.11%
9	Normalized Poly	0.5	36.14%
10	Poly	0.5	3.28%
11	Puk	0.5	28.77%
12	RBF	0.5	15.96%
13	Normalized Poly	3	11.97%
14	Poly	3	0.85%
15	Puk	3	28.78%
16	RBF	3	1.13%

Figure 4. Actual sales and forecasted sales of SMOreg.

3.4. Forecasting Accuracy Measurement

For evaluating the forecasting accuracy of the three methods mentioned above, 15% of the data patterns is not used in the models for testing purpose and the output of the models are compared with the actual value to calculate mean absolute percentage error (MAPE). Table 3 shows the short-term forecasting accuracy of the applied methods based on MAPE measurement mentioned in section 2.4. The table is a summary of best experiments performed in each method. The MAPE rates are 0.16%,

0.72% and 0.85% for GM (1,1), MLP and SMOreg respectively. According to results GM (1,1) outperformed MLP and SMOreg models by providing lower MAPE value. The superiority of the GM (1,1) is not an unexpected result as it gives successful results with a small amount of data with increasing trend. However, the high forecasting accuracy of ANN vs SVM shows that these methods can also be applied in cases where there is little historical data with trend.

Table 3. MAPE value of GM (1,1), MLP and SMOreg.

Models	MAPE
GM (1,1)	0.16%
MLP	0.72%
SMOreg	0.85%

5. Conclusions

In recent years sales forecasting has been critical for determining major activities and strategic decisions of companies. The sales volumes of many companies are likely to be positively or negatively affected by extraordinary circumstances. The pandemic has been an unprecedented example of these extraordinary situations and people started to pay much more attention to their health than ever before, and therefore, they began to buy products that will boost their health. The increased purchase of these products has positively impacted some specific food industries. The company worked in this paper operates in the referred food industry and requires a guiding method to deal with their increasing sales.

In the light of above, a short-term estimate was made for a food supplement product of the company. GM (1,1), ANN and SVM are assessed as sales forecasting tools, which are known as intelligent machine learning methods. All the models have been developed with their own optimization parameters. ANN and SVM experiments were conducted in WEKA environment. The accuracies of the employed methods were compared using the MAPE criteria. The MAPE results show that all the models gave superior results, with the GM (1,1) slightly better than ANN and SVM. The challenge of this study is that due to the novelty of the pandemic situation, very little historical data is available. Therefore, it is not surprising that the GM (1,1), which gives very successful results with limited data is superior one. However, it should not be ignored that ANN and SVM also gave very successful results.

While forecasting is essential for decision makers in normal conditions, more robust methods is required in existence of extraordinary situations like pandemic. This paper examines the usability of three intelligent forecasting models by employing increasing sales data of the relevant company affected by pandemic. The above-mentioned findings show that the company can replace the legacy forecasting method with these intelligent forecasting methods, especially with GM (1,1).

For further studies, the proposed models can be applied also for forecasting other products in different fields such as personal care products and organic products, which have an increasing sales trend due to pandemic or any other reason. In this way, companies will benefit from accurate results of models, holding too much or too little inventory can be prevented and, as a result, costs can be reduced.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Wang, C-H., Yun, Y. Demand planning and sales forecasting for motherboard manufacturers considering dynamic interactions of computer products. *Computers & Industrial Engineering* **2020**, *149*. DOI: https://doi.org/10.1016/j.cie.2020.106788.

[2] Chu, C-W., Zhang, G.P. A comparative study of linear and nonlinear models for aggregate retail sales forecasting. *Int. J. Production Economics* **2003**, *86*, 217–231. DOI: https://doi.org/10.1016/S0925-5273(03)00068-9.

[3] Abolghasemi, M., Hurley, J., Eshragh, A., Fahimnia, B. Demand forecasting in the presence of systematic events: Cases in capturing sales promotions. *Int. J. Production Economics* **2020**, *230*. DOI: https://doi.org/10.1016/j.ijpe.2020.107892.

[4] Yu, Y., Choi, T-M., Hui, C-L. An intelligent fast sales forecasting model for fashion products. *Expert Systems with Applications* **2011**, *38*, 7373–7379. DOI: https://doi.org/10.1016/j.eswa.2010.12.089.

[5] Tsoumakas, G. A survey of machine learning techniques for food sales prediction. *Artif Intell Rev* **2019,** *52*, 441–447. DOI: https://doi.org/10.1007/s10462-018-9637-z.

[6] Tarallo, E., Akabane, G., Shimabukuro, C.I., Mello, J. Amancio, D. Machine learning in predicting demand for fast-moving consumer goods: An exploratory research. *IFAC PapersOnLine* **2019**, *52, (13)*, 737–742.

[7] Ansuj, A.P., Camargo, M.E., Radharamanan, R., Petry, D.G. Sales forecasting using time series and neural networks. Computers Ind. Engng **1996**, *31*, 421-424.

[8] Kotsialos, A., Papageorgiou, M., Poulimenos, A. Holt-winters and neural-network methods for medium-term sales forecasting. Proceedings of 16th Triennial World Congress, Czech Republic, Elsevier IFAC Publications **2005**, 133-138.

[9] Tanaka, K. A sales forecasting model for new-released and nonlinear sales trend products. Expert Systems with Applications **2010**, *37*, 7387-739. DOI: https://doi.org/10.1016/j.eswa.2010.04.032.

[10] Kandananond, K. A comparison of various forecasting methods for autocorrelated time series. International Journal of Engineering Business Management **2012**, *4, (4)*. DOI: https://doi.org/10.5772/51088.

[11] Choi, T-M, Hui, C-L, Ng, S-F., Yu, Y. Color trend forecasting of fashionable products with very few historical data. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), **2012**, *42, (6)*, 1003-1010.

[12] Yu, X., Zhiquan, Q., Yuanmeng, Z. Support vector regression for newspaper/magazine sales forecasting. *Procedia Computer Science* **2013**, *17*, 1055-1062. DOI: https://doi.org/10.1016/j.procs.2013.05.134.

[13] Du, X-F., Leung, S-C-H., Zhang, J-L, Lai, K-K. Demand forecasting of perishable farm products using support vector machine. *International journal of systems Science* **2013**, *44, (3)*, 556-567. DOI: https://doi.org/10.1080/00207721.2011.617888.

[14] Kitapcı, O., Özekicioğlu, H., Kaynar, O., Taştan, S. The effect of economic policies applied in Turkey to the sale of automobiles: multiple regression and neural network analysis. *Procedia-Social and Behavioral Sciences* **2014**, *148*, 653-661. DOI: https://doi.org/10.1016/j.sbspro.2014.07.094.

[15] Xia, M., Wong, W.K. A seasonal discrete grey forecasting model for fashion retailing. *Knowledge-Based Systems* **2014**, *57*, 119-126. DOI: http://dx.doi.org/10.1016/j.knosys.2013.12.014.

[16] Di Pillo, G., Latorre, V., Lucidi, S., Procacci, E. An application of support vector machines to sales forecasting under promotions. *4OR-QJ Oper Res* **2016**, *14*, 309-325. DOI: https://doi.org/10.1007/s10288-016-0316-0.

[17] Vhatkar, S., Dias, J. Oral-care goods sales forecasting using artificial neural network model. *Procedia Computer Science* **2016**, *79*, 238-243. DOI: https://doi.org/10.1016/j.procs.2016.03.031.

[18] Karmy, J.P., Maldonado, S. Hierarchical time series forecasting via support vector regression in the European travel retail industry. *Expert Systems with Applications* **2019**, *137*, 59-73. DOI: https://doi.org/10.1016/j.eswa.2019.06.060.

[19] Güven, İ, Şimşir, F. Demand forecasting with color parameter in retail apparel industry using artificial neural networks (ANN) and support vector machines (SVM) methods. *Computers & Industrial Engineering* **2020**, *147*. DOI: https://doi.org/10.1016/j.cie.2020.106678.

[20] Zhang, Mu., Huang, X-R., Yang, C-B. A Sales Forecasting Model for the Consumer Goods with Holiday Effects. *Journal of Risk Analysis and Crisis Response* **2020**, *10, (2)*, 69-76. DOI: https://doi.org/10.2991/jracr.k.200709.001.

[21] Ahmetoğlu Taşdemir, F., Şeker, S. Fuzzy Time Series and Grey Theory Forecasting for the Sales of Cleaning Products. International Conference on Intelligent and Fuzzy Systems, **2021**, Istanbul, 24-26.08.2021, Turkey, Springer, 641-648.

[22] Deng, J.-L. Control problem of grey system. *Systems and Control Letters* **1982**, 1, (5), 288-294. DOI: https://doi.org/10.1016/S0167-6911(82)80025-X.

[23] Ene, S., Öztürk, N. Grey modelling-based forecasting system for return flow of end-of-life vehicles. *Technological Forecasting and Social Change* **2017**, *115*, 155-166. DOI: http://dx.doi.org/10.1016/j.techfore.2016.09.030.

[24] Wang, C-H. Predicting tourism demand using fuzzy time series and hybrid grey theory. *Tourism Management* **2004**, *25*, 367-374. DOI: https://doi.org/10.1016/S0261-5177(03)00132-8.

[25] Toğa, G., Atalay, B., Toksari, M.D. Covid-19 Prevalence forecasting using autoregressive integrated moving average (ARIMA) and artificial neural networks (ANN): Case of Turkey. *Journal of infection and public health* **2021**, *14*, 811-816. DOI: https://doi.org/10.1016/j.jiph.2021.04.015.

[26] Ballı, S. Data analysis of Covid-19 pandemic and short-term cumulative case forecasting using machine learning time series methods. *Chaos, Solitons & Fractals* **2021**, *142*. DOI: https://doi.org/10.1016/j.chaos.2020.110512.

[27] Vapnik, V., Chervonenkis, A. A note on one class of perceptrons. *Automation and Remote Control* **1964**, *25.*

[28] Merlini, D., Rossini, M. Text categorization with WEKA A survey. *Machine Learning with Applications* **2021**, *4*. DOI: https://doi.org/10.1016/j.mlwa.2021.100033.

[29] Ballı, S. Data analysis of Covid-19 pandemic and short-term cumulative case forecasting using machine learning time series methods. *Chaos, Solitons & Fractals* **2021**, *142*. DOI: https://doi.org/10.1016/j.chaos.2020.110512.

[30] Shevade, S., Keerthi, S., Bhattacharyya, C., Murthy, K. Improvements to the SMO algorithm for SVM regression. *IEEE Trans. Neural Network*s **2000**, *11, (5)*, 1188-1193.

[31] Meenal, R., Selvakumar, A. I. Assessment of SVM, empirical and ANN based solar radiation prediction models with most influencing input parameters. *Renewable Energy* **2018**, *121*, 324-343. DOI: https://doi.org/10.1016/j.renene.2017.12.005.

[32] Lewis, C.D. Industrial and Business Forecasting Methods. Butterworths-Heinemann, London,**1982**.

[33] Jena, P. R., Majhi, R., Kalli, R., Managi, S., Majhi, B. Impact of Covid-19 on GDP of major economies. Application of the artificial neural network forecaster, *Economic Analysis and Policy* **2021**, *69*, 324-339. DOI: https://doi.org/10.1016/j.eap.2020.12.013.

[34] Villavicencio, C. N., Macrohon, J. J. E., Inbaraj, X. A., Jeng, J- H., Hsieh, J- G. Covid-19 Prediction applying supervised machine learning algorithms with comparative analysis using WEKA. *Algorithms* **2021**, *14*. DOI: https://doi.org/10.3390/a14070201.

[35] Witten, I. H., Frank, E., Hall, M. A., Pal, C. J. Data Mining Practical machine learning tools and techniques, Elsevier, 4th Edition, **2017**.