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Sales Forecasting Using Convolution Neural Network

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ABSTRACT

Sales forecasting is an essential component of business management, providing insight into future sales and revenue. It is critical for effective inventory management, cash flow, and business growth planning. While many retailers rely on simple Excel functions or subjective guesses from management, the industry is increasingly turning to machine learning techniques to develop more accurate and reliable prediction models. Among these techniques, Convolutional Neural Networks (CNN) emerged as a suitable option due to their ability to learn and improve accuracy over time. CNN applies several layers to make predictions, adjusting their weights with each input data point to minimize prediction error. As a result, sales forecasting with neural networks can significantly improve market operations and productivity for businesses. The validity of the proposed model is compared with the Facebook Prophet method, which is known as the recent time series forecasting method.

1. Introduction

Sales forecasting is the process of estimating future sales or revenue for businesses. It is an integral part of business management and plays a substantial role in identifying the potential sales trends of products for business improvement, and it has recently gained immense popularity to boost market operations and productivity due to new technologies. Sales forecasts are usually updated monthly, quarterly, half-annually, or annually. Without a solid idea of how future sales will look, stock inventory, cash flow, and the plan for business growth may not be easily manageable. When it comes to forecasting sales, most retail shops or suppliers rely on a simple function in Excel, sometimes simply based on their head of management's liking or even wild conjectures. These forecasts are important for determining profitable retail operations to meet customer demand, maintain storage levels, and identify probable losses for the businesses.

The industry has traditionally focused on a conventional statistical model, yet in recent years, machine learning techniques have received more attention in creating the prediction model for

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forecasting sales. Machine learning is an area of artificial intelligence (AI) and computer science that focuses on using data and algorithms to imitate human ways of learning, gradually improving its accuracy. Machine learning works with three main parts, which include the decision process, the error function, and the model optimization process.

The neural network algorithms, specifically the Convolutional Neural Networks (CNN) and Facebook Prophet (FB Prophet) methods, are used in developing sales forecasting models. There are many machine learning techniques to be taken into consideration when developing the sales forecasting model. LeCun *et al*. [1] stated that CNN is a deep learning technique that has gained prominence in image processing and face recognition. On the other hand, FB Prophet is a powerful open-source tool for time-series forecasting that is widely used in retail industry [2]. It offers flexibility in modelling time-series data by incorporating domain-specific knowledge and seasonality [2]. Several studies have shown that both CNN and FB Prophet can be effective in predicting sales [3-4].

Sales forecasts are essential for companies because they can prevent resource waste, eliminate avoidable losses, and enable methodical planning for production, inventory, and marketing strategies based on the projection. Additionally, precise sales forecasts can enhance customer service going forward and spur business expansion, which will benefit the economy of the nation. Economic freedom and income per capita or economic growth are strongly correlated, according to earlier studies [5]. Therefore, in order for company to perform effectively, sales forecasting is crucial.

There are various methods available for sales forecasting, each with advantages and disadvantages. Some popular methods include Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Facebook Prophet (Fb Prophet).

Time-series forecasting models ARIMA and SARIMA are frequently employed for predicting sales in the literature. These models can handle stationary and non-stationary data because they are based on autoregressive and moving average approaches. Both models have limitation to deal with non-linear pattern hidden in a time series. Machine learning techniques like CNN and LSTM have gained popularity due to their ability to handle enormous datasets and spot non-linear patterns in the data. Therefore, in this study, we propose the CNN model to forecast weekly and monthly sales time series data. In order to evaluate which approach is more effective for sales forecasting, we compare the performance of the CNN and the FB Prophet technique in this study.

2. Literature Review

2.1 Overview of Sales Forecasting Techniques

Sales forecasting is an essential task for businesses of all sizes, enabling them to make informed decisions about production, inventory, staffing, and pricing. Various techniques are available for forecasting sales, and the choice of method depends on several factors, such as the type of data available, the forecasting horizon, the level of accuracy required, and the computational resources available [6].

Time series analysis is used in sales forecasting to examine previous sales data, discover patterns and trends, and apply those findings to project upcoming sales [7]. Time series analysis techniques include moving averages, exponential smoothing, and ARIMA (Auto Regressive Integrated Moving Average) models [8]. The ARIMA model is a predictive statistical model that can detect autocorrelation, seasonality, and trend in time series data and use it to make predictions [9].

One of the machine learning methods that can be helpful in identifying data patterns and used in classification, prediction, and forecasting is the neural networks model [10]. Neural networks can be trained using historical sales data and other sales-influencing elements including marketing campaigns, promotions, and seasonal influences [11].

Deep learning approaches, such as LSTM, have gained favour for sales forecasting in recent years due to their ability to capture long-term relationships in time series data [12]. In order to analyse time series data with long-term dependencies, LSTM is a variation of recurrent neural networks (RNNs) that has the ability to selectively retain or forget past information [13].

The Facebook Prophet algorithm, created by Facebook's Core Data Science team [2], is another efficient way for predicting sales. The algorithm is built on an additive model that incorporates trend, seasonality, and holiday impacts and is capable of handling both trend changes and outliers [2]. Due to its simplicity of use, tolerance to outliers, and capacity for handling missing data, the method has grown in popularity.

Apart from these techniques, other methods are available for sales forecasting, such as regression analysis, exponential smoothing, and econometric models. Every technique has advantages and disadvantages, and the best approach relies on the particular issue and available information [7].

In summary, sales forecasting is a critical task for businesses, and there are various techniques available for predicting future sales. Time series analysis, neural networks, and deep learning techniques, such as LSTM, are some of the popular methods used for sales forecasting [6].

2.2 Traditional Forecasting Methods: ARIMA and SARIMA

Traditional statistical techniques that are frequently used for time series forecasting, particularly sales forecasting, include Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA). An ARIMA model was used by Sandhya and Radha [14] to predict sales for several product categories in the Indian retail industry. The SARIMA model takes into consideration the seasonal component of the time series, whereas the ARIMA model is based on the assumption that future values of a time series may be predicted based on its past values and built on the regression approach. Three elements make up the ARIMA model: moving average (MA), differencing (I), and autoregression (AR).

The SARIMA model, which takes seasonality in time series data into account, is an extension of the ARIMA model. Since the SARIMA model can handle data with seasonal patterns, it is frequently employed in sales forecasting. For instance, Arunraj and Diane [15] employed the SARIMA model in the food retail industry for predicting the monthly sales of bananas depending on various characteristics.

Although the SARIMA models are effective at detecting trends and seasonal patterns in data, they fall short when dealing with complex patterns like non-linear trends, abrupt changes in the data, and exogenous influences like weather and consumer behaviour. These elements help to design cutting-edge methods for sales forecasting, including CNN.

2.3 Convolutional Neural Networks (CNN)

CNN is an effective method in the field of image processing [16]. Consequently, employing CNN to sales forecasting is suggested because CNN have shown amazing success in a variety of disciplines. The deep learning algorithms known as CNN is able to recognize patterns and characteristics in the input data. CNN has been created to enhance conventional statistical models including sales forecasting. For instance, Sarvesh *et al*. [17], employed a CNN model to forecast future sales by forecasting the amount of stock in the Brazilian retail business using data from the Yahoo Finance API.

Sarvesh *et al*. [17] proposed a hybrid model that combines a CNN with Long Short-Term Memory (LSTM) to predict stock prices. The authors utilized a dataset consisting of historical stock prices and technical indicators for several companies listed on the Indian stock exchange. They pre-processed the data and trained the hybrid model to predict the closing price of the following trading days. The results showed that the proposed model outperformed the traditional time-series models.

The authors [18] also presented a hybrid model using CNN and the LSTM approach to forecast future sales for large-scale retailers. The authors used a dataset that included sales information for a range of products in India. The data was pre-processed, and the CNN-LSTM model was trained to forecast future sales. The outcomes demonstrated that the suggested model performed better than the conventional LSTM technique.

2.4 Facebook Prophet (FB Prophet)

The FB Prophet model is a recent time series model that is applicable in various domains, such as forecasting suicide cases in India [19]. The FB Prophet model an applies additive regression model that accounts for seasonal trends, holidays, and other factors that may affects sales. The model is flexible and can handle both non-linear trends and as well as missing data.

The FB Prophet approach was used by Kumar and Shilpa [20] to forecast daily and year sales for a supermarkets chain. The research discovered that, in terms of precision and usability, the Prophet model performed better than other conventional forecasting techniques like ARIMA.

Likewise, Ghareeb *et al*. [21] forecasted daily retail sales for various sorts of stores in several towns and states across the nation using the FB Prophet approach. The authors conducted comparison research of several approaches, and the results shown that the Prophet model had a forecasting accuracy of 92.83%.

The Facebook Prophet approach has generally demonstrated a good model that can be used in a variety of businesses and has grown in popularity because of its simplicity and capacity for accurate forecasting. However, it is vital to highlight that the optimal forecasting method is determined by the nature of the data and the forecasting task at hand.

3. Methodology

Convolutional Neural Networks (CNN) is an extension of the Artificial Neural Network (ANN) commonly used in image processing, video recognition, speech recognition, and text analysis. Generally, CNN consists multiple layers, including input, convolution, pooling, full connection, and output layer. Each layer has its own calculation technique to produce a certain output at a specific threshold. Although the authors of [22] stated that three convolution layers can provide optimal performance, we employ only one convolution layer because adding more layers only increases complexity but provides no performance benefit. In this study, a 1D-CNN is applied because this research involves a one-dimensional time series data. Therefore, sequential data is required.

3.1 Feature extraction in convolution layer

CNN architecture basically has two main layers: feature extraction which consists of convolution layer, and prediction layer. The convolutional layer forms a kernel of neurons with a certain height, width, and thickness. There can be multiple layers of convolutional, each layer being the output of the previous layer and the input of the next layer. The activation value of each kernel in the convolution layer also known as the feature map, can be calculated as Eq. (1) as follows [23]:

$$FM(m) = \sum_{ci=0} \quad C(ci) * I_{(c1+ji)} \tag{1}$$

where *FM* represents feature map, *I* represents input, *C* represents convolution filter at position *c* concerning the i^{th} index, *ji* represents location of the feature map and *m* is used to index the *FM*.

Then, the properties that can influence the output of a convolution layer is calculated as Eq. (2).

$$output = \frac{N-F+2P}{s} + 1 \tag{2}$$

where *N* is input size, *F* is kernel size, *P* is padding, and *s* is stride.

Once the feature map is obtained, in the convolution stage, the Rectified Linear Unit (ReLU) is calculated to transform the negative value to zero. The activation function of ReLU is calculated as Eq. (3).

$$f(x) = (0, x) \tag{3}$$

Pooling is the process to reduce the size of a feature map to estimate a subregion by taking the value of maximum pooling or average pooling.

3.2 Forecasting Layer

The forecasting layer is composed of several layers of interconnected neurons called a multi-layer perceptron (MLP). This MLP contains an input layer, a hidden layer, and an output layer. The output of the feature extraction layer is fed into the final layer. There is a computational method that involves the weight and bias settings that control the accuracy quality in the hidden layer and output layer.

In this study, we split two different experimental works into weekly and monthly forecasting and applied them to both CNN and FB prophet models. We used a Python programming tool to execute this experiment. For the first experiment using the CNN model, we constructed a one-dimensional convolutional neural network (CNN) model to apply data consisting of a univariate time series forecast. Other characteristics of the CNN built with Keras in Python include the following:

i. Input layer: the input data is aggregated to represent one value of sales totals per week or month.
ii. 1D convolution layer: we defined a convolutional layer with 254 filter maps, and a kernel size of 2.
iii. Max pooling layer: we defined a size of 2 for this layer to minimize the data overfitting.
iv. Flatten layer: Data is flattened into a one-dimensional array before being entered into the following layer. The result of the convolutional layers is flattened to make one feature vector.
v. Optimizer: We applied the Adam optimizer to fit this CNN model.

4. Result and Discussion

4.1 Experimental Data

The dataset used in this paper is a time series dataset for sales forecasting, which is publicly available on Kaggle [24]. The dataset contains daily sales data for a period of three years, from

January 2013 to October 2015, for a particular store. The sales data is provided in the form of a time series, where each data point represents the daily sales for a particular product in the store.

The dataset consists of 11 data fields, including ID, shop_id, item_id, item_category_id, item_cnt_day, item_price, date, date_block_num, item_name, shop_name, and item_category_name. The ID field represents a (shop, item) tuple within the test set, while shop_id, item_id, and item_category_id are unique identifiers of a shop, product, and item category, respectively. The item_cnt_day field indicates the number of products sold, and the item_price field represents the current price of an item. The date field indicates the date in the format dd/mm/yyyy, while date_block_num is a consecutive month number used for convenience, with January 2013 being 0, February 2013 being 1, and so on, up to October 2015, which is 33. Finally, the item_name, shop_name, and item_category_name fields provide the names of the product, shop, and item category, respectively.

The goal of this study is to forecast the sales amount using the dataset, which spans from January 2013 to October 2015. These data samples were divided at random into a training set and a test set, with a ratio of 70:30.

4.2 Assessing Model Performance

This section describes the results of the comparison of the CNN and FB Prophet models on a weekly and monthly basis.

The model's performance is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which are typically used to estimate the error difference between the actual and predicted values.

Figures 1-3 display various weekly forecasting outcomes for periods of 13, 26, and 52 weeks, respectively. Figures 4-6 display various forecasting outcomes for 3 months, 6 months, and 12 months using the CNN approach on a monthly basis. The blue line represents the actual sales, and the red line represents the predicted sales.

Figures 1-3 depict graphs that show how the CNN model will perform in the future. In Figure 1, the CNN model is used to forecast sales for the next 13 weeks, while in Figures 2 and 3, the CNN model is used to forecast sales for the next 26 and 52 weeks, respectively, where the 26 weeks correspond to a 6-month period and the 52 weeks correspond to a 1-year period.

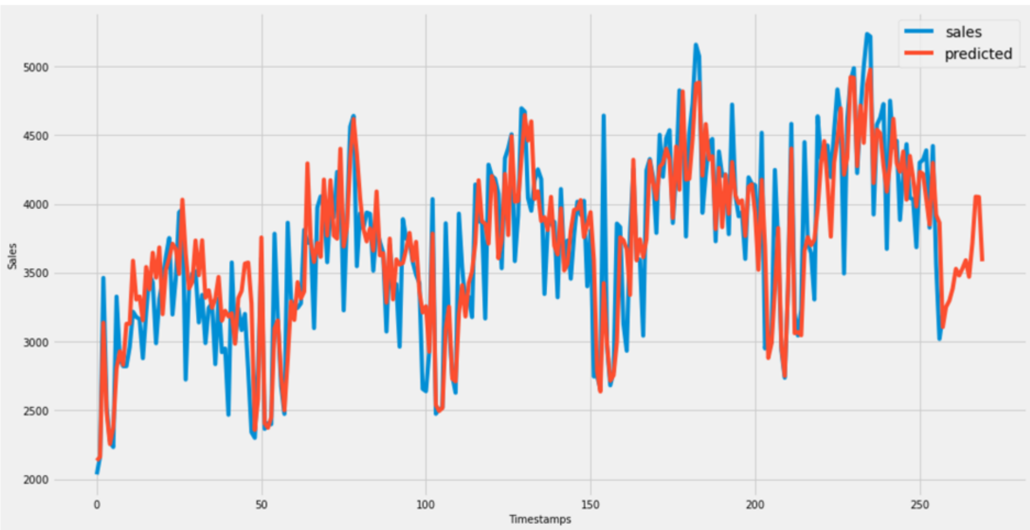

Fig. 1. Results of a 13-week forecast using the CNN model

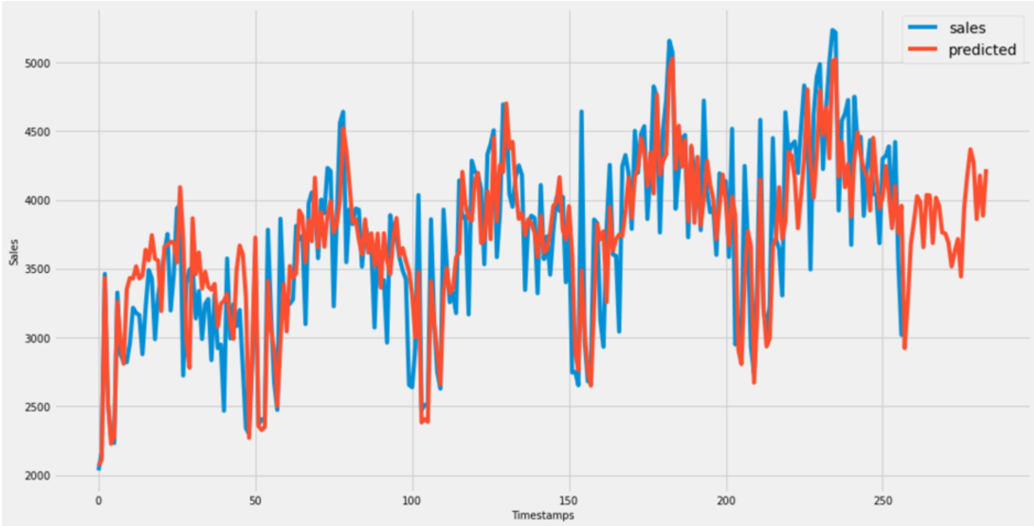

Fig. 2. Results of a 26-week forecast using the CNN model

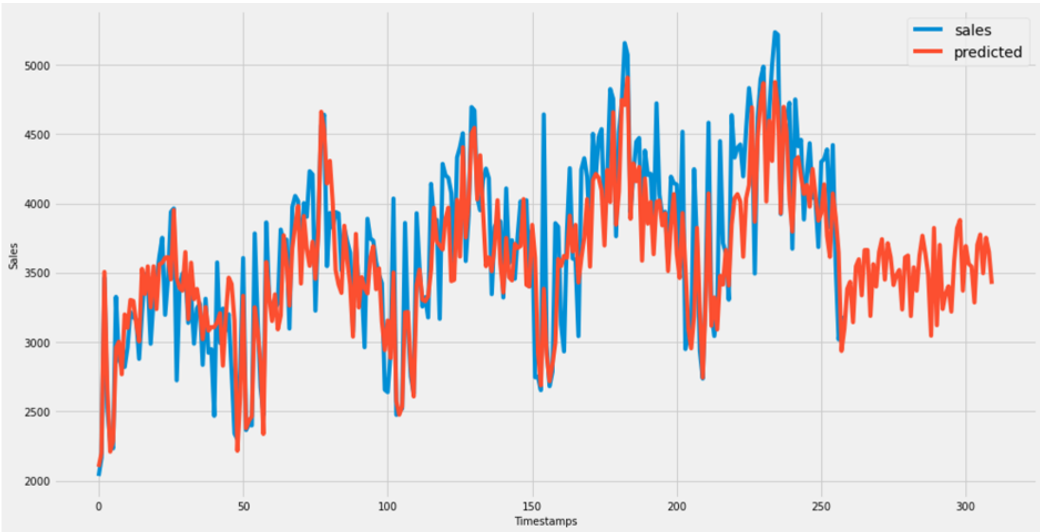

Fig. 3. Results of a 52-week forecast using the CNN model

Figures 1-3 indicate that when the CNN model is applied to historical data, the predicted sales closely match the trend of the actual data. The pattern of predicted sales demonstrates a significant variation in future forecasting, particularly for the one-year weekly estimate.

Figures 4 - 6 depict graphs that show how the CNN model will perform in the future for monthly forecasting. In Figure 4, Figure 5 and Figure 6, the CNN model is used to forecast sales for the next 3 months, 6 months, and 12 months. Figures 4-6 also show that, when employing the CNN model on historical data, the predicted sales closely follow the pattern of the actual data. For future forecasting, the patterns of forecasted sales exhibit more variations.

Fig. 4. Results of a 3-month forecast using the CNN model

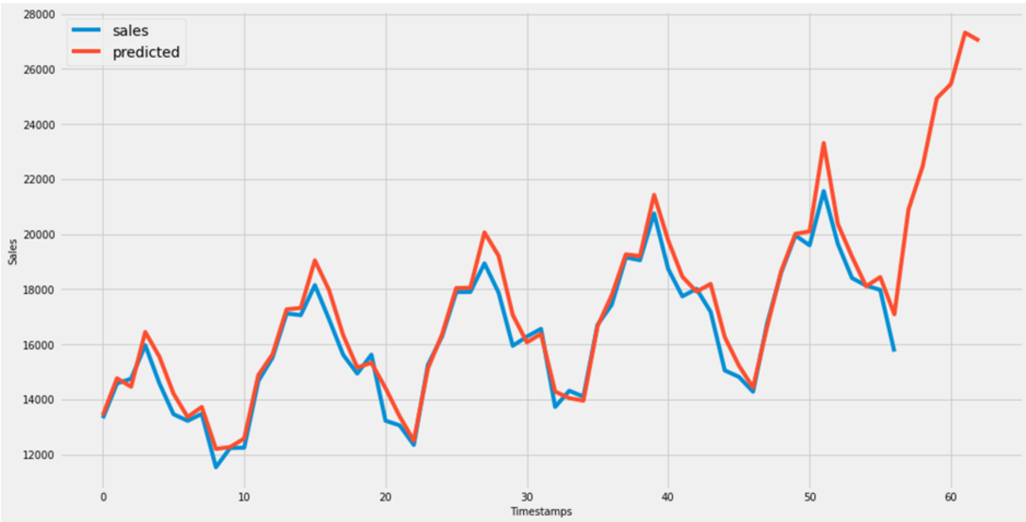

Fig. 5. Results of a 6-month forecast using the CNN model

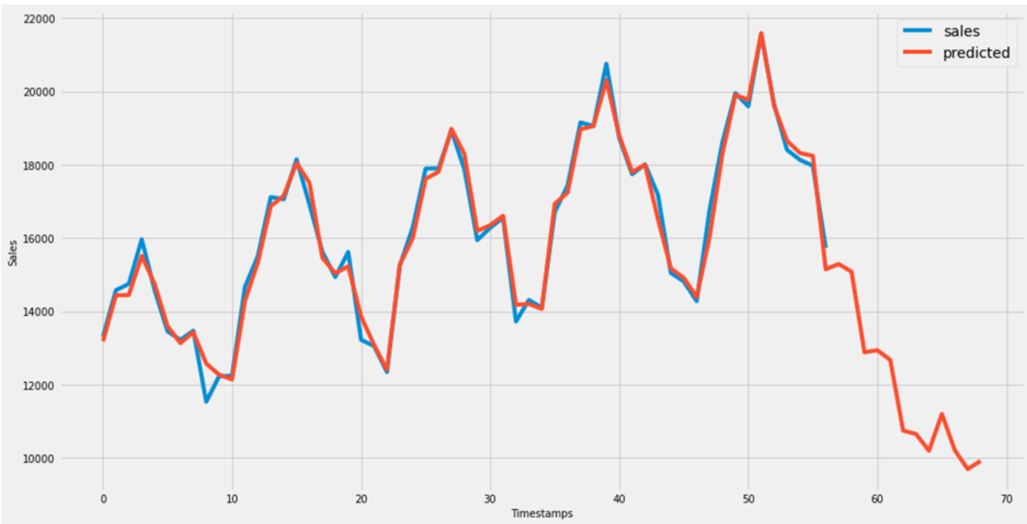

Fig. 6. Results of a 12-month forecast using the CNN model

In the next experiments, we employed the FB Prophet model to fit weekly and monthly data. Figures 7-9 depict weekly graphs that show how the FB Prophet model will behave to forecast the sales amounts for the next 13 weeks, 26 weeks, and 52 weeks, respectively. The black dots represent the actual data, the blue line represents prediction, and the lighter blue band represents uncertainty intervals. These forecasting plots seem to show that the model performs well in finding the seasonal pattern, and the forecasted sales follow the trends over the last three years.

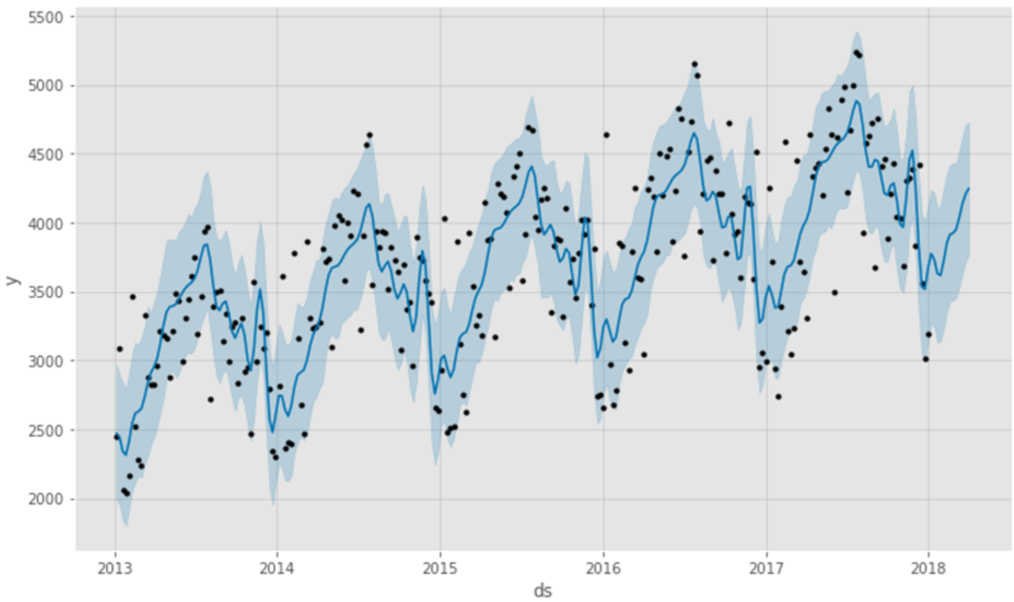

Fig. 7. Results of a 13-week forecast using the FB Prophet model

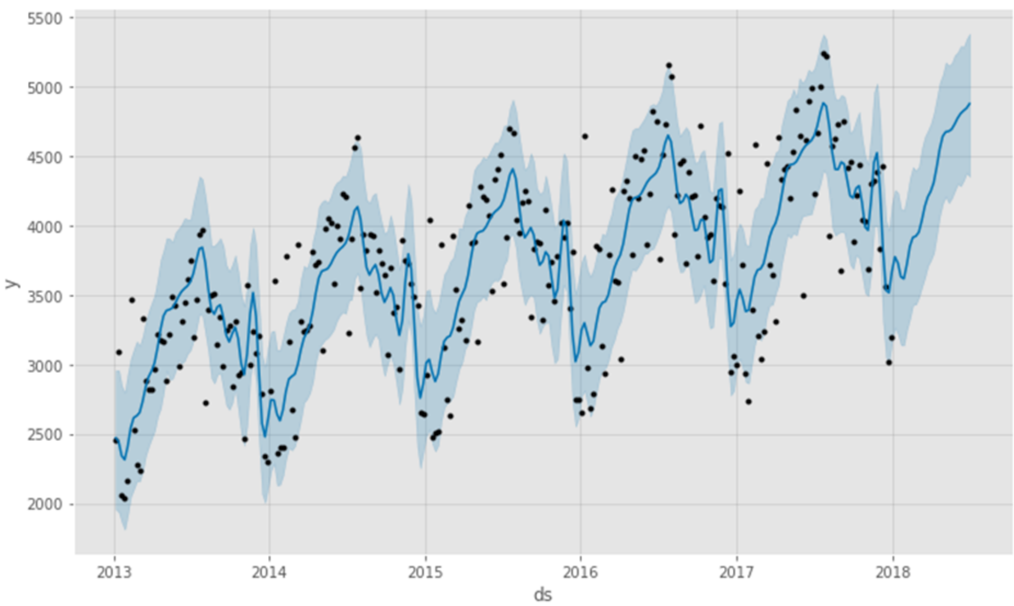

Fig. 8. Results of a 26-week forecast using the FB Prophet model

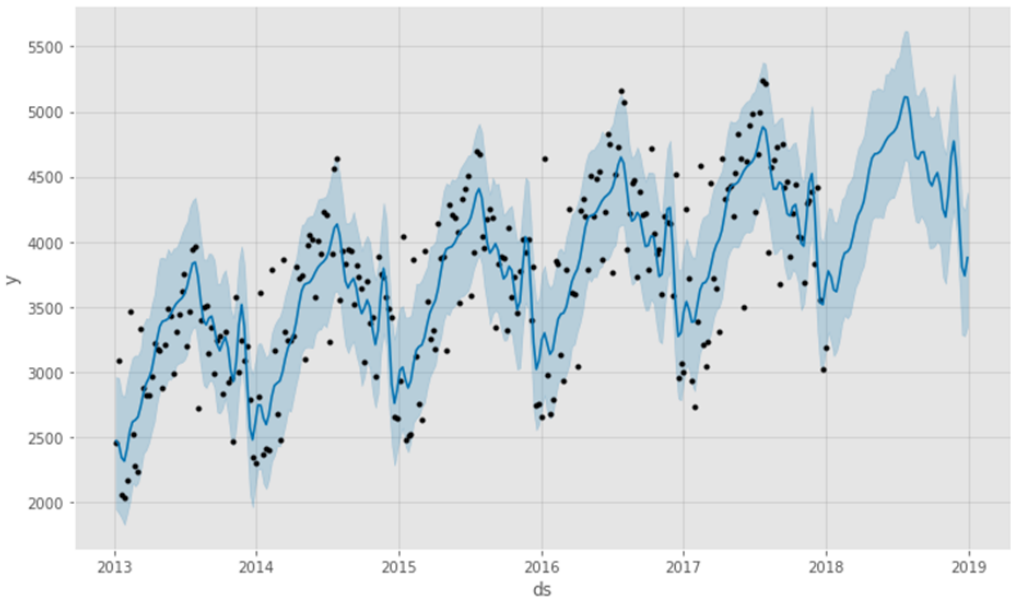

Fig. 9. Results of a 52-week forecast using the FB Prophet model

In these experiments, we also provide MAE and RMSE results to measure errors in forecasting as presented in Table 1.

Table 1
MAE & RMSE scores for both methods using different parameter values on weeks and months

Method	Forecast	MAE	RMSE
CNN	13 weeks	**245.7**	**339.34**
	26 weeks	**276.8**	**366.51**
	52 weeks	**255.12**	**342.5**
	3 months	604.32	906.6
	6 months	473.67	634.75
	12 months	220.05	305.66
FB Prophet	13 weeks	307.25	385.54
	26 weeks	307.25	385.54
	52 weeks	307.25	385.54
	3 months	**261.81**	**316.13**
	6 months	**261.81**	**316.13**
	12 months	**261.81**	**316.13**

MAE is a popular accuracy metric for evaluating the accuracy rate of forecasting results since it is simple to calculate and understand. The CNN algorithm is used to predict sales for the next 13 ,26 and 52 weeks. The MAE value of 245.7, 276.8 and 255.12 indicates that, on average, the predictions using CNN model are better than using the FB prophet model which the values is 307.5 for weekly forecasting.

The RMSE value of 339.34, 366.51 and 342.5 indicates that the model's predictions had an average error of 339.34, 366.51 and 342.5 units for the weekly forecasting. However, all values of MAE and RMSE using FB prophet are consistent in each of the 13 weeks, 26 weeks, and 52 weeks.

For the weekly forecast, the CNN model shows the best scores compared to the FB Prophet since it generates lower units of average errors on MAE and RMSE results. The lower the MAE value, the higher the accuracy of the model.

Normally, the result of RMSE is never greater than MAE. The results in Table-1 also prove that the MAE always yields a smaller rate than the RMSE.

Likewise, in the evaluation of the RMSE result, CNN outperformed on the weekly forecasting result compared to FB Prophet, which performed better on the monthly forecasting result.

4. Conclusions

Convolutional Neural Network (CNN) is composed of an input layer, a convolutional layer, a pooling layer, a full connection layer, and an output layer. This paper proposed weekly and monthly forecasting using 1DCNN and compared the results with univariate FB Prophet on the sales data from 2013 to 2018. The results suggest that CNN has the best scores at weekly forecasting, while FB Prophet has the best scores at monthly forecasting. However, in terms of result consistency, the FB Prophet shows more consistency in MAE and RMSE in various parameters on weekly and monthly data.

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