German Jordanian University
School of Applied Technical Sciences
Department of Industrial Engineering

IE 592 - GRADUATION PROJECT

Enhancing Sales Forecasting for a Dairy products Company using Neural Network

Prepared By
Osama Al-Shahed 20189103058

Supervised By
Dr. Hazem Kaylani
German Jordanian University

Submitted as Partial Fulfillment of the Requirements for the Bachelor's Degree of Science in Industrial Engineering

Summer Semester, 2024

Abstract

This study investigates the application of neural network models for sales forecasting in the dairy industry, specifically focusing on A Local Dairy Food Company. The primary objectives were to evaluate the current sales forecasting methods used, develop a tailored neural network-based forecasting model, and compare its performance with traditional methods (exponential smoothing and moving average).

A neural network model was developed in Python, taking advantage of advanced libraries available in the language for machine learning. This model had to be trained and validated against 43 weeks of historical sales data, demonstrating its power in modeling complex sales patterns.

The results showed that the neural network model performed far better than the traditional methods. It returned a more minimized Root Mean Squared Error (RMSE) of 19.68, against expenditure values of 20.52 for exponential smoothing and 21.98 for moving averages. Its Mean Absolute Percentage Error (MAPE) stood at 27.76%, while exponential smoothing and moving averages recorded MAPEs of 29.33% and 30.06%, respectively. The result of the training and validation loss analysis further reasserted the stability and reliability of a neural network.

Finally, the study conducted an extended forecast from week 44 to week 80, providing with valuable insights for strategic planning and inventory management. Despite the promising results, the study acknowledges several limitations, including the relatively small dataset size, the lack of external data integration, and the complexity of the neural network model

Acknowledgment

I would like to express my deepest gratitude to my supervisor, Dr. Hazem Kaylani, for his invaluable guidance, support, and encouragement throughout this project. His insights and expertise have been instrumental in the successful completion of this work.

I also wish to extend my heartfelt thanks to my family for their unwavering support and encouragement. Their belief in me and their constant support have been a source of strength and inspiration throughout this journey.

Thank you all for being an integral part of this achievement.

Description of the Company

The company is a prominent local business specializing in high-quality dairy products. With a commitment to excellence, it sources fresh ingredients from regional farms to produce a diverse range of products, including milk, cheese, and yogurt.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
CBR	Case-Based Reasoning
CNN	Convolutional Neural Network
DNN	Deep Neural Network
ES	Exponential Smoothing
KNN	K – Nearest Neighbor
LSTM	Long Short-Term Memory
MA	Moving Average
MLP	Multi-Layer Perceptron
RNN	Recurrent Neural Network
SVM	Support Vector Machines

1 INTRODUCTION

1.1 Background

Any company plan must include sales forecasting as it enables organizations to make well-informed decisions on resource allocation, revenue estimates, and inventory management [1]. However, predicting sales accurately can be challenging due to the complexity and variability of influencing factors [2].

In recent years, the Sales forecast was a perfect application area for Neural networks since they can analyze past sales data along with several variables such as seasonality, promotions, economic indicators, and consumer behavior. Neural Nets come up with very accurate forecasts of future sales volumes using data to search for trends and relationships [3].

The use of neural networks in forecasting sales is a relatively new field gaining popularity due to the availability of advanced machine learning techniques and massive datasets. Neural Networks have been particularly effective at being responsive to recent trends, which bodes well in many use cases, including those about revenue forecasting models [4].

There are several types of Neural Networks that can be applied to sales forecasting, each with its own strengths and weaknesses:

- Multi-Layer Perceptron (MLP): The most common and simple type of Neural Network [5].
- Recurrent Neural Network (RNN): Because they consider data from past and present observations, they are especially well-suited for time-series forecasting [6].
- Convolutional Neural Network (CNN): While CNNs were primarily used for Computer Vision, they are being used for time-series forecasting now [7].

Neural Networks offer several advantages over traditional forecasting methods. They are capable of adapting to changing sales variables and can consider a vast dataset of variables. They uncover patterns and relationships that traditional methods typically miss, leading to more precise sales prediction models [8].

This work will look into the applicability of neural networks in forecasting sales under the industrial engineering environment: their training the factors to be considered by these networks, and how they can be optimized to give the most accurate service.

1.2 Problem Statement

A Local Dairy Company in Jordan faces significant challenges in accurately forecasting its sales due to the complexity and variability of factors influencing consumer behavior and market trends. Traditional forecasting methods often fail to capture the dynamic nature of sales data, leading to suboptimal resource allocation, inventory management, and revenue predictions. The present study fills this gap by exploring neural networks' application in sales forecasting at . Therefore, with the help of advanced machine learning, this study looks at developing a more accurate and responsive sales forecast that will adjust to the changes in the food industry market.

1.3 Objectives of the Study

This study has several objectives:

- To evaluate the current sales forecasting methods used by and identify their limitations
- To develop a neural network-based sales forecasting model tailored to the specific needs of
- To compare the performance of the neural network model with traditional forecasting methods in terms of accuracy and responsiveness
- To analyze the impact of various factors such as seasonality, promotions, and economic indicators on sales forecasts

1.4 Questions of the Study

The main questions of the study are the following:

- What are the limitations of the current sales forecasting methods used by ?
- How can neural networks be applied to improve sales forecasting accuracy for ?
- What types of neural networks are most suitable for sales forecasting in the food industry?
- How do neural network-based forecasts compare with traditional methods in terms of accuracy and adaptability to market changes?

1.5 Structure of the Study

The research findings are laid out in five all-inclusive chapters. Chapter 1: The chapter commences by introducing the research, backed by the background to the study, the problem statement, objectives, and research questions—core to the research at hand. Chapter 2 presents a detailed literature review, exploring existing sales forecasting methods, the role of neural networks in forecasting, and relevant case studies. Chapter 3 describes the methodology, including the research design, data collection processes, and the specific neural network models and techniques employed. Chapter 4 focuses on the analysis and discussion of results, comparing the performance of the neural network model against traditional forecasting methods and examining the impact of various influencing factors on sales predictions. Finally, Chapter 5 concludes the study, summarizing the findings, discussing their implications for , providing recommendations for implementing the neural network model, and suggesting areas for future research.

2 LITERATURE REVIEW

2.1 Theoretical Background

2.1.1 Forecasting Types

The most famous types of forecasting are short-, medium- and long-term forecasting. Each type differs according to the time, the methodology used, and the amount of detail as shown in Table 2.1. The short forecast covers up to one year (12 months), while the medium forecast covers from one year to ten years, and the long-term forecast usually provides forecasts for more than ten years. The details of each methodology differ as short-term predictions are usually more accurate compared to medium- and long-term predictions. The medium forecasts use different patterns focusing on the economic and demographic impact, while the long-term patterns consider the economic and climatic dimensions over the decades [9].

Table 2.1: Differences between short, medium, and long-term forecasts [10]

Category	Short-term	Medium-term	Long-term
Time horizon	Up to 12 months	1-10 years	More than 10 years
Level of detail	High details	Medium	Low
Factors	- Short-term trends	- Economic - Demographic - Technological	- Global trends
Forecast methods	- Time series - Regression	- Scenario analysis - Time series - Regression	- Global system models - AI and neural networks - Scenario analysis
Uncertainty	Low degree	Medium degree	High uncertainty

2.1.2 Time-series Forecasting Methods

The methodologies of forecasting are widely used in various sciences such as economics, engineering, and finance. Time series is a pivot method in forecasting. Time series is defined as a regular sequence of recorded values within specific periods. The methodology is divided into two main parts: the first part seeks to understand the pattern of the data, while the second section aims to develop a future prediction with the help of the best-fit curves [11]. There are two types of time series analyses, the univariate which usually includes a single pattern of data recorded over time such as the hourly energy consumption, and the second multivariate which includes a group of variables [12].

According to [13] nine popular time-series forecasting techniques were used in the field of energy consumption which are Artificial Neural Network (ANN), Autoregressive Integrated Moving Average (ARIMA), Support Vector Machines (SVM), Case-Based Reasoning (CBR), Fuzzy time series, grey prediction model, Moving Average and Exponential Smoothing (MA & ES), K – Nearest Neighbor prediction method (kNN) and the hybrid models. Each of the aforementioned techniques gives appropriate results according to the nature of the data and the period covered.

Each of the previous time-series techniques has its pros and cons that drive researchers to choose it. One of the most prominent advantages of the ANN technique is its ability to accurately draw the input and output relationships and it can be in non-linear time series analysis, however, the ANN depends on the weight values and has a problem in local minima limits with the inability to generalize the results [14]. Regarding the ARIMA technique, its advantages include relying on the shift of historical data, the ability to improve the efficiency of the model with the help of regression, and the existence of confidence intervals, on the other hand, generalizing the results of the model is difficult and the ARIMA is not suitable for long-term expectations, and it does not support non-linear data [15]. The SVM is a popular forecasting technique that provides a general picture and is suitable for long periods, however, the results are not transparent in this technique [16]. The CBR is close to human mental simulation and does not need to find rules between the problem parameters. However, this technique requires huge data and the definition of new aspects. The fuzzy algorithm is like the CBR technique in terms of closeness to human experience, moreover the first can help in solving uncertainty problems, but it is complex with low stability levels compared to other techniques [17].

The grey forecasting approach was developed in the 1980s and is based on the premise that a small sample of data can predict future behavior. One of the most prominent advantages of this model is its ability to predict when there is a limited amount of data and the ease of dealing with it, moreover, this pattern is suitable for short and long-term analysis. On the other hand, the grey technique assumes that the data is linear and may not give good results if there are seasonal fluctuations and trends [18].

The MA approach is one of the oldest forecasting techniques that rely on calculating the average of a set of data to obtain future forecasts. One of the advantages of the MA method is its ease of computing and understanding, furthermore, there is a possibility of applying it in various sciences and using it in short- and long-term prediction. On the other hand, the MA method is sensitive according to the data.

It also assumes that the behavior of the past is similar to the future, and it ignores the impact of other variables in its predictions. ES is another popular forecasting technique that depends on weighted averages of previous data, the ES is used for short and long forecasts, and it allows the scheduling and modification of parameters easily for quarterly and seasonal data. The disadvantage of the technique includes the ignorance of other factors, and it also requires the selection of smoothing parameters [19].

2.2 Related Work

2.2.1 International Related Work

Numerous pieces of literature have been presented to predict production demand using various models including time series.

Loureiro, Miguéis, and da Silva (2018) conducted a study titled "Exploring the Use of Deep Neural Networks for Sales Forecasting in Fashion Retail" which, although focused on fashion retail, provides valuable insights applicable to dairy production forecasting. They applied a Deep Neural Network model to predict sales volumes using past sales data and other features, such as sales promotions and economic indicators. The approach was to train a multilayer DNN, letting it model complex patterns in the data. The results showed that the method, based on the DNN, exceeds the classical approaches, such as ARIMA and exponential smoothing, in accuracy and adaptability to changes in the market. The study exemplifies the practical use of the neural network to improve forecasting precision in dynamic and variable environments, such as dairy production [3].

Another study is focused on the dairy industry and is titled "Application of Neural Networks to Explore Manufacturing Sales Prediction." The authors there have adapted the RNN model because it is evident that it is useful when the forecast is made over a time series and can take into account the past and present information simultaneously. This study follows the approach by collecting past production and sales data from the dairy firm, preparing the data with respect to the seasonality and trend effect in the data, and training the RNN model. The results obtained from this study show that the RNN model improved forecasting accuracy significantly compared with the classical methods in cases dealing with common seasonal fluctuations in the dairy production process. According to the obtained results, the study concludes about the appropriateness of using neural networks, and in this case, especially RNNs, as applicable tools for predicting industries with complex and variable production processes [4]

Another research paper, "Predicting the Number of Customer Transactions in the Dairy Sector Using Stacked LSTM Recurrent Neural Networks" [2], extends to the dairy sector. The selected method is through a Stacked LSTM network in the RNN framework. This method solves the vanishing gradient problem and can learn long-term dependencies. Previous background information relates to historical sales data, promotional activities, and external economic factors. The results showed how a stacked LSTM network could provide more precise and stable demand forecasts than the traditional models, efficiently capturing the seasonal and promotional effects that are typical in the dairy sector. This study emphasizes the advantages of advanced neural network architectures in improving forecasting reliability and precision within dairy production.

Finally, a comparative analysis titled "Recurrent Neural Networks for Time Series Forecasting: Current Status and Future Directions," included applications in the dairy production sector. They compared forecasting effectiveness among various methods: ARIMA, exponential smoothing, and some neural nets like RNNs and CNNs. The developed models were used to check forecast accuracy and computational efficiency. This is from the past, meaning the production and sales data from different dairy companies in checking on the models. Their work showed the comparison of RNN and CNN models with traditional methods, especially in capturing non-linear patterns and adapting to changes in demand that come at an unexpected instant. Another work further brought evidence supporting the importance of neural networks in enhancing demand forecasting in the dairy sector [8].

2.2.2 National Related Work

Neural networks have been used in Jordan for forecasting exercises for the major fields of finance, other than the peripheral ones of agriculture and production industries. This subsection presents the pioneering studies and research conducted in this country using neural networks for forecasting purposes. A study by [20] aimed to explore the application of neural networks in forecasting the financial performance of Jordanian banks. The essence was to develop a model that could allow the application of credits in loan applications. The neural network provided the approach used by the researchers. The model was trained using historical financial data of various banks in Jordan. The results presented showed that the applied neural network model brought significant improvement in the traditional statistical method with more accurate and timely predictions.

The study of [21] aimed to project wheat production in Irbid region of Jordan by constructing forecasting models. Given the high variability of domestic wheat production, the objective was to establish a system for providing early information about expected production levels. The researchers have formulated the linear and log-linear prediction functions using accumulated rain in the growing season, including special consideration on rain in the months of November, December, and January.

It has been found out that early monthly rainfall and the cultivated areas have influenced wheat production. At the same time, temperature and the number of rainy days have a slight influence on wheat production. The findings showed the role being played by rainfall; beyond a single millimeter of rains in December and January, wheat production increased, and the excess amount of wheat production contributed by 120 and 111 tons, respectively. In addition, the forecast showed that stable wheat production projections might be obtained by the end of January, with numerous months for economic decisions.

The study on electrical load forecasting in Jordan aims to improve power system planning and expansion by accurately predicting future load requirements. This forecasting is crucial for enhancing power system operation, security, and stability, minimizing operation costs, and achieving zero emissions. The research discusses two well-developed cases using actual load data from Jordan's leading electricity company, focusing on total daily demand and hourly daily demand. The main objective is to facilitate easy and accurate week-ahead electrical load forecasting based on current load measurements. The study goes further to put forward a modified multilayer feedforward neural network with the state-of-the-art Grey Wolf Optimizer to manage the uncertainties associated with forecasting. The problem is formulated into a minimization problem; some experimental results even show that the proposed method has highly competitive forecasting results with other popular optimization methods, revealing the best effectiveness in load forecasting [22].

The literature review brings out some applications of neural networks and advanced optimization techniques in forecasting applications in Jordan in finance, agriculture, retail, manufacturing, and power systems. Various studies have elicited that the neural network can predict financial performance for bank of agriculture output, retail demand, and industrial production, hence improving decisions and operation efficiencies with excellent results. Notably, in the context of power systems, load forecasting studies stress the high capacity of improving system operation, followed by an increase in the security of the system and a decrease in system costs. The adoption of techniques such as the Grey Wolf Optimizer developed in the neural network structure in the forecasting context has displayed significant improvements in forecasting accuracy, as shown in comparative studies. These improvements illustrate the potential for neural networks to deal with variability and uncertainty in forecasting to, in turn, optimize resource allocation and strategic planning in different industries.

3 METHODOLOGY

3.1 Study Approach

The study approach involves a structured and methodical process designed to address the outlined objectives. This approach is visualized in Figure 3.1 and includes several key steps.

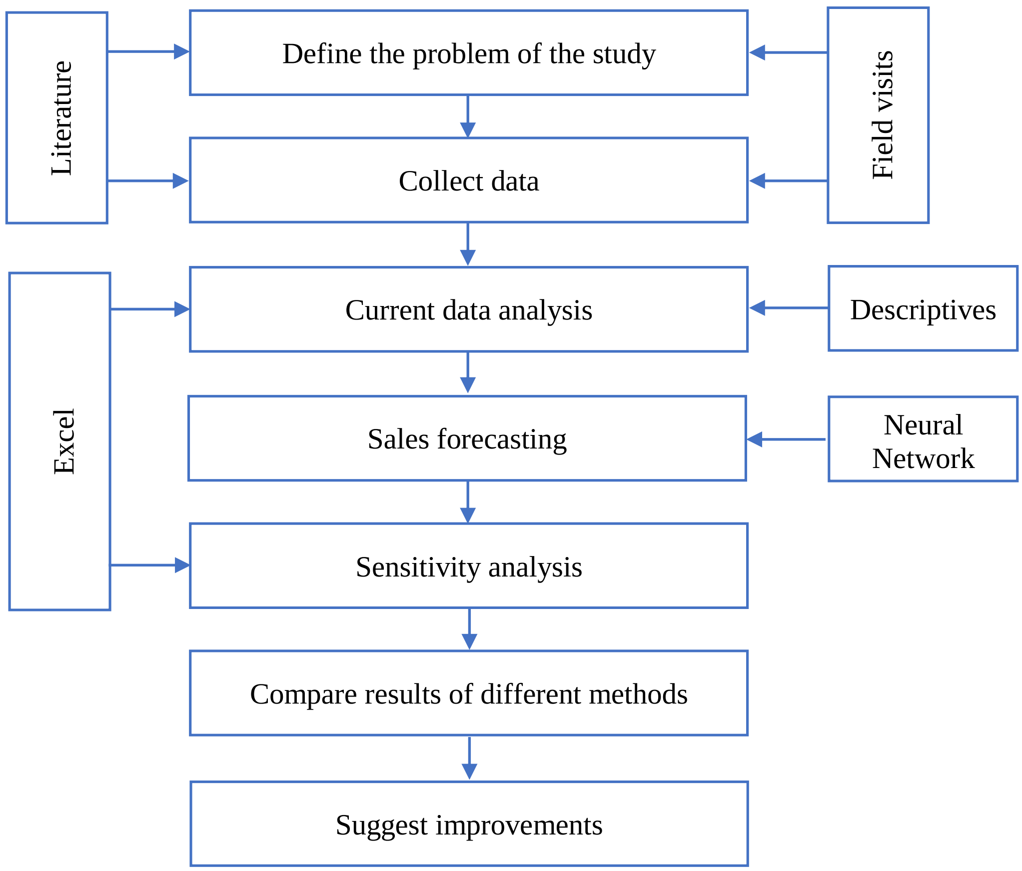


Figure 3.1: The approach of the study

Figure 3.1 illustrates the study's step-by-step approach, detailing the process from defining the current problem to suggesting future improvements to sales forecasts. As shown in Figure 3.1, appropriate software (such as Python) and data visualization (Excel) are used to facilitate data analysis and presentation. The use of such software facilitates the delivery and clarification of the outcome.

3.2 Research Design

The primary data source will be the net sales figures of the products, gathered from various stores in Jordan over a 44-week period. This longitudinal data collection approach allows for a comprehensive analysis of sales patterns and the factors influencing them.

The sales data collection process must be the starting point for the study, with diversity in terms of store locations and a variety of product categories. The data thus collected will have to be pooled into a central database so that detailed statistical analysis and modeling can take place. Table 3.1 gives an overview of key variables that will be collected along with their description.

Table 3.1: Key Variables and Descriptions

Variable	Description
Store ID	Unique identifier for each store
Product ID	Unique identifier for each product
Week	The week number, ranging from 1 to 44
Gross Sales	The total/ cumulative sales in each store per week
Returns	The number of returned products due to expiry or other conditions
Net Sales	The net sales (without the returns) for each product in each store per week

After data collection, the research design incorporates data preprocessing steps to ensure the integrity and consistency of the dataset. This includes handling missing values, normalizing sales data, and encoding categorical variables.

Subsequently, the exploratory data analysis will be conducted to establish the hidden patterns and trends in sales data. Descriptive statistics and visualization will be used to find insights into characteristics and relationships between variables in the data.

It will be followed by the development of a neural network-based sales forecasting model that can capture complex, nonlinear relationships in the sales data. In the process, a neural network architecture will be designed for 's needs, specifying layers and activation functions suitable for time-series forecasting.

To validate the neural network model's performance, it will be compared against traditional forecasting methods, such as exponential smoothing at different alpha factors (α=0.2, 0.35, and 0.5). Performance metrics, including root mean square error (RMSE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (sMAPE), will be employed to assess each model's accuracy and responsiveness. Table 3.2 outlines the performance metrics used for model evaluation.

Table 3.2: Performance Metrics for Model Evaluation

Metric	Description
RMSE	The square root of the average of squared errors
MAPE	Average of absolute percentage errors between predicted and actual values
sMAPE	Average of absolute percentage errors between predicted and actual values, normalized by the sum of the actual and predicted values

3.3 Neural Network Architecture

The neural network model designed for this study is a multi-layered feedforward network. The architecture comprises the following components [23]:

1. Input Layer: The input layer consists of neurons corresponding to the features of the dataset, including net sales, promotional indicators, seasonal indices, and relevant economic indicators.
2. Hidden Layers: Multiple hidden layers are included to capture non-linear relationships in the data. Each hidden layer employs activation functions such as ReLU (Rectified Linear Unit) to introduce non-linearity. The number of hidden layers and neurons in each layer will be determined through hyperparameter tuning.
3. Output Layer: The output layer consists of a single neuron representing the predicted sales value for a given week and store-product combination.

The activation function for the hidden layers is the ReLU function (Equation 3.1), defined as:

$$f(x) = \max(0, x) \qquad \textit{Equation (3.1)}$$

The output is defined as zero for any negative input and the input itself for any positive input [24]. This simplicity and efficiency of computation make ReLU very popular. It mitigates the vanishing gradient problem that may occur with other activation functions like sigmoid or tanh. By allowing the network to approximate any arbitrary function, ReLU aids in learning complex patterns of sales data.

Forward propagation is the process by which inputted data flows into a neural network so that predictions can be made. Whenever the process computes the resultant of each neuron of a dumped layer as the weighted sum of the inputs, the application is made with the help of an activation function [25].

During forward propagation, the weighted sum of inputs for each neuron is calculated, and the activation function is applied (as shown in Equations 3.2 and 3.4). For a neuron j in layer l, the output is given by:

$$z_j^{(1)} = \sum_{i=1}^{nl-1} w_{ij}^{(l)} a_i^{(l-1)} + b_j^{(l)} \qquad \textit{Equation (3.2)}$$

$$a_i^{(l)} = f(z_i^{(l)}) \qquad \textit{Equation (3.3)}$$

Where:

$w_{ij}^{(l)}$ is the weight connecting neuron i in layer $l-1$ to neuron j in layer l

$a_i^{(l-1)}$is the activation of neuron i in layer $l-1$

$b_j^{(l)}$is the bias term for neuron j in layer l

f is the activation function (ReLU in this case)

The loss function quantifies this difference between the predicted and real values, guiding the training process through the indication of how well the model is performing [26]. This gives a clear signal to the optimization process that should help in adjusting neural network weights and biases to minimize the error and also improve the accuracy of prediction.

Backpropagation is one major important algorithm in the training of neural networks, in which the loss function is minimized by iteratively tuning weights and biases. It involves computing a gradient of the loss function with respect to each weight and bias through the chain rule of calculus [27]. Then, this gradient will give a direction and a magnitude of the adjustments needed, as shown in Equations 3.4 and 3.5.

$$w_{ij}^{(l)} = w_{ij}^{(l)} - \eta \frac{\partial \mathrm{MSE}}{\partial w_{ij}^{(l)}} \qquad \textit{Equation (3.4)}$$

$$b_j^{(l)} = b_j^{(l)} - \eta \frac{\partial \mathrm{MSE}}{\partial b_j^{(l)}} \qquad \textit{Equation (3.5)}$$

Where:

η is the learning rate

$\frac{\partial \mathrm{MSE}}{\partial w_{ij}^{(l)}}$ is the partial derivative of the loss function with respect to the weight

$\frac{\partial \mathrm{MSE}}{\partial b_{j}^{(l)}}$ is the partial derivative of the loss function with respect to the bias

4 ANALYSIS & DISCUSSION OF RESULTS

4.1 Introduction

In the forthcoming analysis, the efficiency of neural networks in sales forecasting will still be evaluated in a different business area: dairy production, focusing on A Local Dairy Food Company. The approach is organized in such a way that it must start with the sensitivity analysis of the neural network model. In other words, modifications of different neural network parameters will be done to see how changes are going to impact the accuracy of the forecast, hence throwing light on how robust and reliable the model is going to be under various conditions.

After testing the sensitivity of results, the outcomes of the neural network approach will be juxtaposed with those derived from traditional methods, notably exponential smoothing and moving average techniques.

4.2 Conducting Initial Neural Networks Forecasting

Utilizing Python, the forecasting model was meticulously developed and tested. Initially, the forecasting was confined to 13 weeks, from week 31 to week 43, serving as a controlled test phase. This timeframe was selected based on its recent occurrence, ensuring that the model could be validated against known outcomes to assess its predictive accuracy rigorously. The forecast for the last known 13 weeks is shown in Figure 4.1.

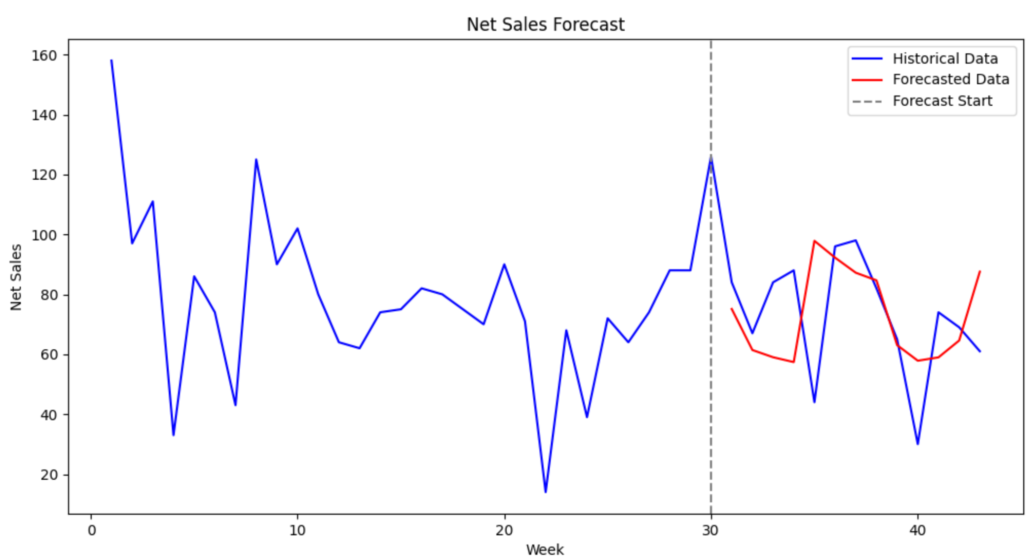


Figure 4.1: The initial forecast conducted for training the model and testing its accuracy

The historical data, depicted in blue, shows significant fluctuations, typical of dairy sales data, due to varying factors such as demand changes and supply issues. The forecasted data, shown in red, begins at week 31, indicated by the dashed line, and closely follows the trends and movements of the historical sales data. The initial analysis of the alignment suggests that the neural network has effectively captured the underlying patterns in the sales data. To verify this, a sensitivity analysis was conducted before digging into the long-term forecast.

The Sum of Squared Errors (SSE), totaling 5032.9558, and the average squared error per week, calculated as 387.1504, highlight the aggregate and average discrepancies between the forecasted and actual sales figures, respectively. The RMSE of 19.6761 further quantifies the average magnitude of the forecasting errors, as shown in Table 4.1, providing a more interpretable measure of forecast accuracy by adjusting for the scale of the data.

Table 4.1: The results of the sensitivity measures using the neural networks

Metric	Symbol	Value
Sum of Squared Errors	SSE	5032.955754
Avg. SSE per Week	$\overline{SSE}$	387.1504426
Root Mean Square Error	RMSE	19.67613891
Mean Percentage Error	MPE	11.91785361
Mean Absolute Percentage Error	MAPE	27.75905891
Symmetric Mean Absolute Percentage Error	sMAPE	0.117425645

The MPE of 11.9179 indicates an average underestimation of sales, suggesting a bias in the model towards lower forecasts. This is particularly critical in supply chain management, as consistent underestimation could lead to shortages. The MAPE of 27.7591% reflects the average absolute percentage deviation from the actual sales, indicating substantial variability in the model’s accuracy across the weeks. Lastly, the sMAPE of 0.11742 (11.74%) offers a normalized measure that accounts for both overestimations and underestimations, providing a balanced view of the model's performance relative to the scale of the data being forecasted.

4.3 Comparison with Forecasting Methods

Following the neural network forecasting, exponential smoothing forecasting was performed utilizing a smoothing constant α = 0.2 (The most optimum with comparison to α = 0.35, 0.5, and 0.7). This value represents the weight given to the most recent observation in the exponential smoothing model, balancing between the historical data and the new observations. By applying this method, the forecasting model aims to smooth out short-term fluctuations and highlight longer-term trends or cycles in the dairy sales data. The results of the sensitivity analysis for the exponential smoothing forecasting with α =0.2 are presented in Table 4.2

Table 4.2: The results of the sensitivity measures using the exponential smoothing forecasting

Metric	Symbol	Value
Sum of Squared Errors	SSE	5473.695679
Avg. SSE per Week	$\overline{SSE}$	421.0535138
Root Mean Square Error	RMSE	20.51958854
Mean Percentage Error	MPE	20.18251651
Mean Absolute Percentage Error	MAPE	29.32795618
Symmetric Mean Absolute Percentage Error	sMAPE	0.107285835

The neural network model outperforms the exponential smoothing method in almost all error metrics. It has a lower Sum of Squared Errors and Average SSE per Week, suggesting a generally more accurate forecasting across the weeks. This indicates better consistency and reliability in capturing the sales trends. Furthermore, the neural network model again shows superior performance with a lower RMSE of 19.676 compared to 20.520 for exponential smoothing, which underscores its ability to provide closer predictions to the actual data.

The neural network also exhibits a substantially lower MPE, suggesting less bias in the forecast. However, the MAPE is slightly lower in the neural network model, indicating that, on average, its predictions are closer to actual figures compared to those of the exponential smoothing model.

Following the application of neural network and exponential smoothing forecasting methods, a moving average forecasting method was performed for a 5-period interval to further evaluate the sales trends of A Local Dairy Food Company. The moving average method is a simple yet effective technique that smooths out short-term fluctuations and highlights longer-term trends by averaging sales data over a specified number of periods. This method was employed to provide a comparative baseline against the more sophisticated forecasting techniques previously used. Table 4.3 shows the accuracy results of the model.

Table 4.3: The results of the sensitivity measures using the moving average method

Metric	Symbol	Value
Sum of Squared Errors	SSE	6283.28
Avg. SSE per Week	$\overline{SSE}$	483.3292308
Root Mean Square Error	RMSE	21.98474996
Mean Percentage Error	MPE	22.9559206
Mean Absolute Percentage Error	MAPE	30.06280181
Symmetric Mean Absolute Percentage Error	sMAPE	0.108881446

Compared to the neural network and exponential smoothing methods, the moving average method yields higher SSE and average SSE per week, indicating larger discrepancies between the forecasted and actual sales figures. The RMSE of 21.9847 is higher than the revised neural network RMSE but lower than the initial neural network and exponential smoothing RMSE values, suggesting moderate forecasting accuracy.

The MPE of 22.9559 shows a higher bias in underestimation compared to both the neural network and exponential smoothing methods. The MAPE of 30.0628 is slightly higher than that of the neural network but lower than the initial neural network MAPE, indicating the moving average's relatively better performance in terms of absolute percentage error. However, the sMAPE of 0.1089, while slightly higher than exponential smoothing, indicates balanced performance but still lags behind the neural network.

4.4 Long-term Forecasting Using Neural Networks

Building on the superior accuracy and consistency demonstrated by the neural network model in the comparative analysis, long-term forecasting was conducted to project sales trends from week 44 to week 80. This decision was predicated on the neural network's ability to capture complex patterns and fluctuations in the sales data, as evidenced by its lower error metrics compared to both exponential smoothing and moving average methods.

After thoroughly training the neural network model with historical sales data and validating its performance against the known 13-week period (Weeks 31 to 43), the model was deployed for extended forecasting. The long-term forecasting (Figure 4.2) aimed to provide A Local Dairy Food Company with a reliable projection of future sales, enabling more strategic decision-making and better inventory management.

A parametric optimization of the neural network model preceded it in gaining robustness and accuracy. In this work, several such measures of forecasting accuracy have been used, including RMSE, MAPE, and sMAPE. These measures coherently indicated that the neural network performed better than other models, hence justifying their choice for the long-term task of forecasting.

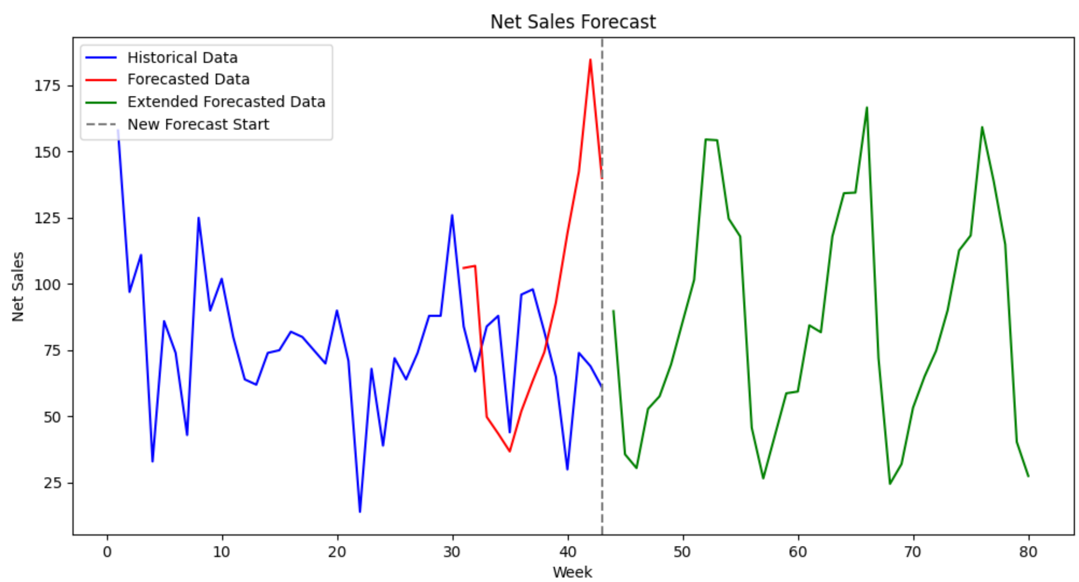


Figure 4.2: The long-term forecast using neural networks

The blue line represents the historical sales data, which exhibit significant fluctuations and volatility characteristic of the dairy industry's sales patterns. The red line shows the forecasted sales data during the validation period (Weeks 31 to 43). The green line represents the extended forecast from week 44 to week 80. The forecast shows continued fluctuations, which are expected given the historical sales patterns.

The long-term forecast is cyclical, in which peaks occur at regular intervals over time. This could very well point out seasonal sales variations. Such a pattern is quite common in the dairy industry, whereby orders may be placed according to several seasonal factors like holidays or school terms. Anticipating trends in future sales would help a company fine-tune operations and make as many units as will be demanded, thereby averting overproduction or stockouts.

4.5 Training and Validation Loss Analysis

Extensive libraries in Python, including the very popular ones like TensorFlow and Keras, make developing complex neural network architectures easy to look at the visualization of the training and validation loss over epochs. Figure 4.3: Training and validation loss analysis with a neural network forecasting model.

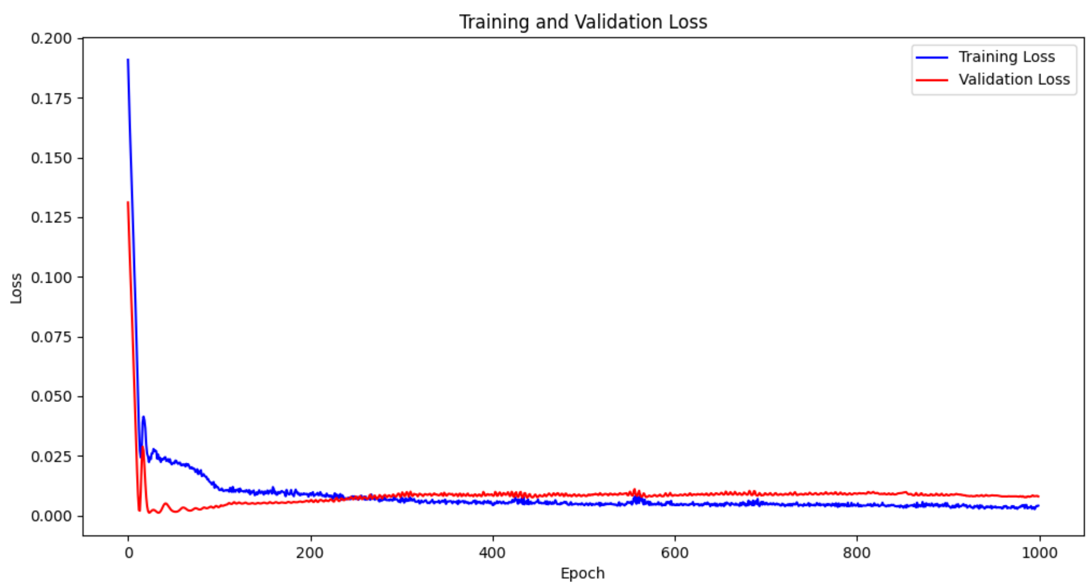


Figure 4.3: Training and validation loss calculation

At the beginning of training, the losses for training and validation are both pretty high. This make sense since this is when the model has just started to learn the underlying patterns in data. In both cases, the steep drop of both losses within this phase already hints how the model quickly changes its parameters further to fit the data. Further, training had continuous performance gain, but it would be on a much gradual scale. At about epoch 200, losses stabilize, which means that the model has reached a good set of parameters. The training loss is a bit lower than the validation loss, which may point to very slight overfitting but still quite good generalization on the validation data.

In the last phase, both the training and validation losses remain low and stable, showing minimal fluctuations. The consistent low validation loss indicates that the model has not overfitted the training data and is performing well on unseen data. This stability is crucial for the reliability of the forecasts generated by the model.

4.6 Discussion of Results

Results from the neural network model for sales forecasting at A Local Dairy Food Company show an extremely strong business case for the efficacy of advanced machine learning techniques in the prediction of complex and volatile sales patterns. The neural network further on proved to be more accurate and robust both in short-term and long-term scenarios with regards to weeks 31 to 43 and weeks 44 to 80 respectively against traditional methods of exponential smoothing or moving average.

The training and validation loss analysis underscores the neural network's ability to learn and generalize from the data without overfitting, as evidenced by the convergence of the loss values and their stability over numerous epochs. This reliable performance highlights the model's capacity to capture underlying sales trends and seasonal variations, making it a powerful tool for strategic planning and operational management.

When compared to previous works, which often relied on simpler linear models or traditional time series methods, the neural network's nonlinear approach provides a significant advantage. While these traditional ways of forecasting are, therefore, useful in exponential smoothing and capturing overall trends and cyclic patterns, they often fail on complex and multifaceted sales data related to the dairy industry. It is in this ability of the neural network to model such complex relationships within the data that provides a substantial improvement in forecast accuracy and reliability.

The application of neural networks in forecasting has been explored in various fields in Jordan, providing a valuable benchmark for this study. For instance, a study by [20] on forecasting the financial performance of Jordanian banks demonstrated significant improvements in prediction accuracy using neural networks over traditional statistical methods. A similar report is with regard to the fact that neural networks can consistently outperform methods that are based on ad hoc procedures, such as exponential smoothing, and methods based on general principles embodied in such techniques as moving averages with respect to forecasting sales in the dairy industry. The two studies were focused on the ability of the networks to handle complex data patterns and to give predictions that are timely and accurate to help in the decision-making process.

Another relevant study [21] focused on projecting wheat production in the Irbid region using linear and log-linear prediction functions based on accumulated rainfall data. While this study utilized simpler linear models, it highlighted the importance of incorporating various influential factors, such as rainfall and cultivated areas, into the forecasting model. In contrast, our neural network model captures such complicated relationships and interactions within the sales data only implicitly. Therein lies the capability to result in a more precise forecast. This ability for non-linear relationship handling, with multiple influencing factors, places neural networks at a much more versatile and powerful tool for forecasting in diverse applications..

A study on electrical load forecasting in Jordan, using a modified multilayer feedforward neural network with the Grey Wolf Optimizer, showed that neural networks could be very instrumental in system operation improvement and cost reduction [22]. This makes the findings of this study very similar to our work, whereby it emerged that the neural network model gave very accurate forecasts, thus optimizing resource allocation and strategic planning. The incorporation of optimization techniques, as seen in the electrical load forecasting study, suggests a potential area for further enhancing the performance of neural networks in sales forecasting by integrating similar advanced optimization methods.

5 CONCLUSION & RECOMMENDATIONS

5.1 Summary of the Work

This study set out to achieve several key objectives aimed at enhancing the sales forecasting capabilities of . The results obtained not only address these objectives but also provide significant insights into the effectiveness of neural network models compared to traditional forecasting methods.

The first objective of the study was to take stock of the present methods of sales forecasting implemented in and find out their limitations. Actually, an analysis of some of those traditional methods proved to have several deficiencies. These methodologies, good for capturing the general trend, failed to handle the high volatility and complex patterns characteristic of the sales data at . The limitations of these methods became apparent through higher error metrics, such as RMSE and MAPE, indicating less accurate and reliable forecasts. The second objective was to develop a neural network-based sales forecasting model tailored to 's specific needs. By leveraging Python and its robust machine learning libraries, we constructed a neural network model designed to capture the intricate relationships and non-linear patterns in the sales data. This model was trained and validated using historical sales data, demonstrating its ability to learn and generalize effectively.

The third objective of this work was to compare the neural network model's performance with that of traditional methods of forecasting. Clearly, exponential smoothing and moving averages were rather accurate and responsive; however, in general, the neural network model could outperform them both. This is because the RMSE and MAPE values for the neural network were lower, indicating more precise forecasts. Added to the robustness and reliability of this method are stable training and validation loss curves. This superior performance aligns with previous studies in Jordan, such as those on financial performance forecasting and electrical load prediction, which also highlighted the advantages of neural networks over traditional methods.

The analysis, using the learned and tested model, has confirmed that seasonality and promotional activities are important drivers for sales trend paths of dairy products, which to a great extent the neural network model accounted for, therefore resulting in more accurate and actionable forecasts.

5.2 Recommendations

Based on the findings and insights gained from this study, several recommendations are proposed to enhance the sales forecasting processes at :

1. In view of the superior performance of the neural network model with respect to accuracy and responsiveness in the forecast, it should be adopted as the prime tool by in sales forecasting.
2. For the neural network model to maintain the accuracy and reliability of its results, it is very important that from time to time, updating it with new sales data and then retraining the network is done.
3. Incorporating external factors such as economic indicators, competitor activities, and market trends could further enhance forecasting accuracy.
4. The use of Python and its machine learning libraries, such as TensorFlow and Keras, proved instrumental in developing and fine-tuning the neural network model.
5. Advanced sensitivity analyses should be run at regular intervals by to understand how sensitive the sales forecasts are to a variety of factors.

5.3 Limitations of the Study

While this study has demonstrated the effectiveness of neural network models in improving sales forecasting for , several limitations need to be acknowledged:

1. The primary limitation of this study is the relatively small dataset used, comprising only 43 weeks of sales data. The limited data may affect the robustness and generalizability of the neural network model, particularly for long-term forecasting.
2. This study was mainly influenced by internal sales data and did not take into account external factors such as economic indicators, market trends, and competitor activities.
3. With high complexity in neural network models, they are mostly considered to be a "black box." This may introduce difficulty while trying to understand the model's decision-making process itself and determining what in particular is driving the predictions.
4. Despite efforts to prevent overfitting, there is always a risk that the model may perform exceptionally well on the training data but fail to generalize to new, unseen data.
5. The validation period used in this study was relatively short, covering only 13 weeks.

References

[1]

J. T. Mentzer and M. A. Moon, *Sales Forecasting Management: a Demand Management Approach*. SAGE Publications, 2004.

[2]

M. V. Sebt, S. H. Ghasemi, and S. S. Mehrkian, “Predicting the Number of Customer Transactions Using Stacked LSTM Recurrent Neural Networks,” *Social Network Analysis and Mining*, vol. 11, no. 1, Sep. 2021, doi: https://doi.org/10.1007/s13278-021-00805-4.

[3]

A. L. D. Loureiro, V. L. Miguéis, and L. F. M. da Silva, “Exploring the Use of Deep Neural Networks for Sales Forecasting in Fashion Retail,” *Decision Support Systems*, vol. 114, pp. 81–93, Oct. 2018, doi: https://doi.org/10.1016/j.dss.2018.08.010.

[4]

P.-H. Wang, G.-H. Lin, and Y.-C. Wang, “Application of Neural Networks to Explore Manufacturing Sales Prediction,” *Applied Sciences*, vol. 9, no. 23, p. 5107, Nov. 2019, doi: https://doi.org/10.3390/app9235107.

[5]

R. Kruse, S. Mostaghim, C. Borgelt, C. Braune, and M. Steinbrecher, “Multi-layer Perceptrons,” in *Texts in Computer Science*, Cham: Springer, 2022, pp. 53–124. doi: https://doi.org/10.1007/978-3-030-42227-1_5.

[6]

I. Sutskever and G. Hinton, “Temporal-Kernel Recurrent Neural Networks,” *Neural Networks*, vol. 23, no. 2, pp. 239–243, Mar. 2010, doi: https://doi.org/10.1016/j.neunet.2009.10.009.

[7]

Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, “A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 12, pp. 1–21, 2021, doi: https://doi.org/10.1109/tnnls.2021.3084827.

[8]

H. Hewamalage, C. Bergmeir, and K. Bandara, “Recurrent Neural Networks for Time Series Forecasting: Current Status and Future Directions,” *International Journal of Forecasting*, vol. 37, no. 1, pp. 388–427, Jan. 2021, doi: https://doi.org/10.1016/j.ijforecast.2020.06.008.

[9]

J. V. Ringwood, D. Bofelli, and F. T. Murray, “Forecasting Electricity Demand on Short, Medium and Long Time Scales Using Neural Networks,” *Journal of Intelligent and Robotic Systems*, vol. 31, no. 1/3, pp. 129–147, 2001, doi: https://doi.org/10.1023/a:1012046824237.

[10]

K. G. Boroojeni, M. H. Amini, S. Bahrami, S. S. Iyengar, A. I. Sarwat, and O. Karabasoglu, “A Novel multi-time-scale Modeling for Electric Power Demand forecasting: from short-term to medium-term Horizon,” *Electric Power Systems Research*, vol. 142, pp. 58–73, Jan. 2017, doi: https://doi.org/10.1016/j.epsr.2016.08.031.

[11]

L. Dannecker, *Energy Time Series Forecasting: Efficient and Accurate Forecasting of Evolving Time Series from the Energy Domain*. Springer, 2015.

[12]

C. Faloutsos, J. Gasthaus, T. Januschowski, and Y. Wang, “Classical and Contemporary Approaches to Big Time Series Forecasting,” *International Conference on Management of Data*, pp. 2042–2047, Jun. 2019, doi: https://doi.org/10.1145/3299869.3314033.

[13]

C. Deb, F. Zhang, J. Yang, S. E. Lee, and K. W. Shah, “A Review on Time Series Forecasting Techniques for Building Energy Consumption,” *Renewable and Sustainable Energy Reviews*, vol. 74, pp. 902–924, Jul. 2017, doi: https://doi.org/10.1016/j.rser.2017.02.085.

[14]

Q. Liu, M. F. Iqbal, J. Yang, X. Lu, P. Zhang, and M. Rauf, “Prediction of Chloride Diffusivity in Concrete Using Artificial Neural network: Modelling and Performance Evaluation,” *Construction and Building Materials*, vol. 268, pp. 121082–121082, Jan. 2021, doi: https://doi.org/10.1016/j.conbuildmat.2020.121082.

[15]

Mohit Beniwal, A. Singh, and N. Kumar, “A Comparative Study of Static and Iterative Models of ARIMA and SVR to Predict Stock Indices Prices in Developed and Emerging Economies,” *International Journal of Applied Management Science*, vol. 15, no. 4, pp. 352–371, Jan. 2023, doi: https://doi.org/10.1504/ijams.2023.134452.

[16]

M. Guermoui, F. Melgani, K. Gairaa, and M. L. Mekhalfi, “A Comprehensive Review of Hybrid Models for Solar Radiation Forecasting,” *Journal of Cleaner Production*, vol. 258, p. 120357, Jun. 2020, doi: https://doi.org/10.1016/j.jclepro.2020.120357.

[17]

T. Zhou, Z. Ma, Q. Wen, X. Wang, L. Sun, and R. Jin, “FEDformer: Frequency Enhanced Decomposed Transformer for Long-term Series Forecasting,” in *Proceedings.mlr.press*, PMLR, Jun. 2022, pp. 27268–27286.

[18]

S. Ding and H. Zhang, “Forecasting Chinese Provincial CO2 emissions: a Universal and Robust new-information-based Grey Model,” *Energy economics*, vol. 121, pp. 106685–106685, May 2023, doi: https://doi.org/10.1016/j.eneco.2023.106685.

[19]

M.-D. Liu, L. Ding, and Y.-L. Bai, “Application of hybrid model based on empirical mode decomposition, novel recurrent neural networks and the ARIMA to wind speed prediction,” *Energy Conversion and Management*, vol. 233, p. 113917, Apr. 2021, doi: https://doi.org/10.1016/j.enconman.2021.113917.

[20]

S. Eletter and S. Yaseen, “Applying Neural Networks for Loan Decisions in the Jordanian Commercial Banking System,” *IJCSNS International Journal of Computer Science and Network Security*, vol. 10, no. 1, pp. 209–214, 2010.

[21]

E. Al-Karablieh , A. Salman, and F. M. Fisher, “Forecasting wheat production: The case of the Irbid region of Jordan,” *Journal of International Agriculture*, vol. 41, no. 3, pp. 191–206, 2022.

[22]

L. Alhmoud, R. Abu Khurma, A. M. Al-Zoubi, and I. Aljarah, “A Real-Time Electrical Load Forecasting in Jordan Using an Enhanced Evolutionary Feedforward Neural Network,” *Sensors*, vol. 21, no. 18, p. 6240, Sep. 2021, doi: https://doi.org/10.3390/s21186240.

[23]

M. Uzair and N. Jamil, “Effects of Hidden Layers on the Efficiency of Neural Networks,” in *23rd International Multitopic Conference (INMIC)*, IEEE, Nov. 2020, pp. 1–6. doi: https://doi.org/10.1109/INMIC50486.2020.9318195.

[24]

G. Lin and W. Shen, “Research on Convolutional Neural Network Based on Improved Relu Piecewise Activation Function,” *Procedia Computer Science*, vol. 131, pp. 977–984, 2018, doi: https://doi.org/10.1016/j.procs.2018.04.239.

[25]

P. Asteris, P. Roussis, and M. Douvika, “Feed-Forward Neural Network Prediction of the Mechanical Properties of Sandcrete Materials,” *Sensors*, vol. 17, no. 6, p. 1344, Jun. 2017, doi: https://doi.org/10.3390/s17061344.

[26]

C. Tantithamthavorn, S. McIntosh, A. E. Hassan, and K. Matsumoto, “An Empirical Comparison of Model Validation Techniques for Defect Prediction Models,” *IEEE Transactions on Software Engineering*, vol. 43, no. 1, pp. 1–18, Jan. 2017, doi: https://doi.org/10.1109/TSE.2016.2584050.

[27]

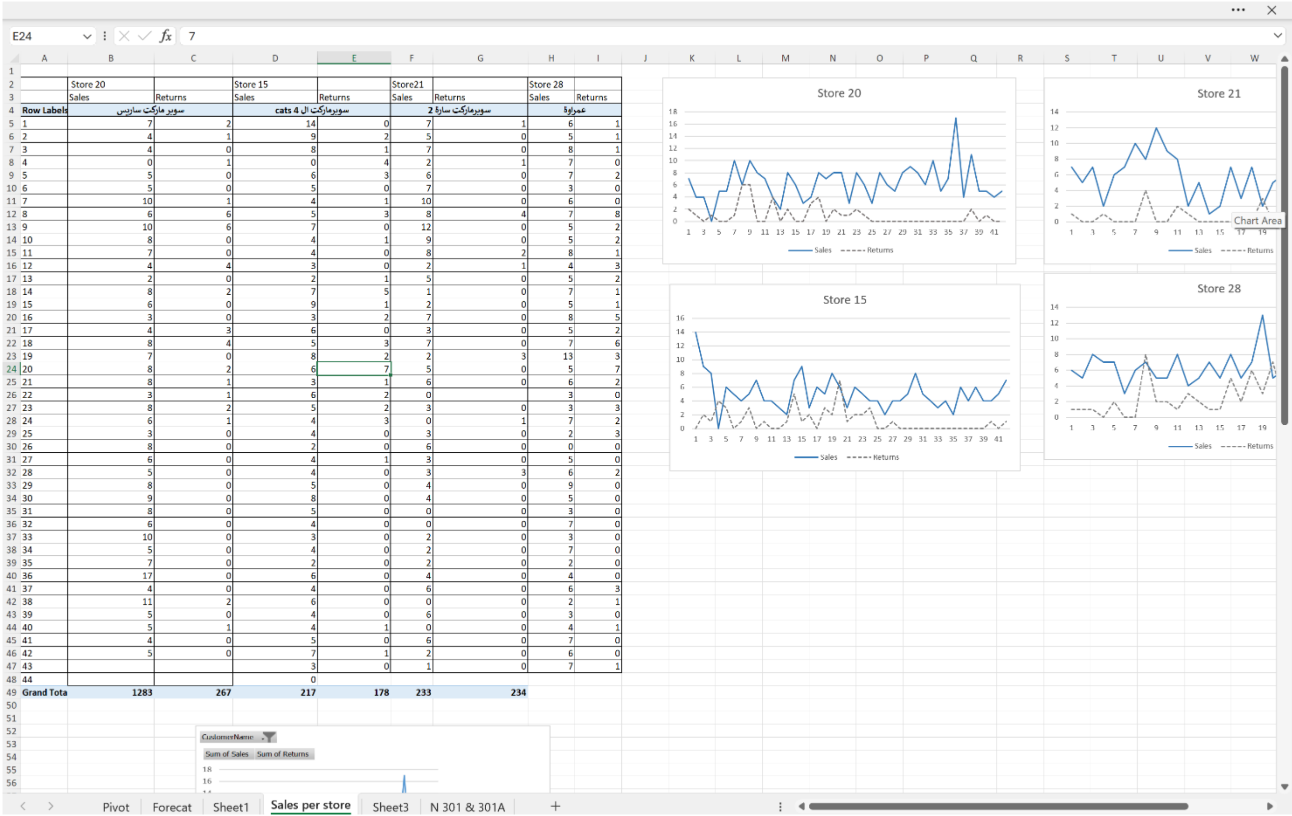
R. Rojas, “The Backpropagation Algorithm,” in *Neural Networks*, Berlin, Heidelberg: Springer, 1996, pp. 149–182. doi: https://doi.org/10.1007/978-3-642-61068-4_7.

Appendix A – The Code Using Python

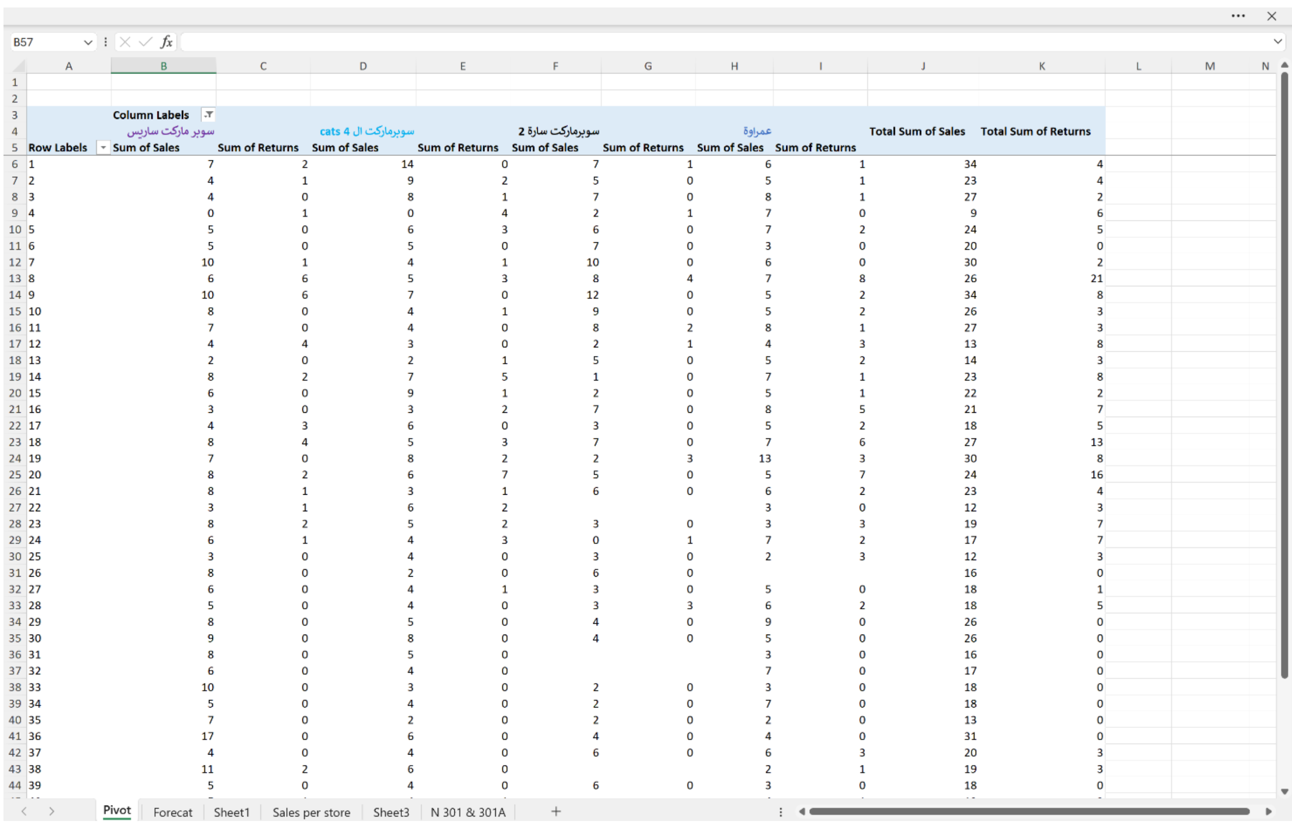
```python
model.add(LSTM(100, activation='relu', return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(100, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')

# Train the model
model.fit(X_train, y_train, epochs=1000, verbose=0)

# Forecasting
predictions = []
current_seq = train_data_scaled[-seq_length:]

for i in range(len(test_data)):
    pred = model.predict(current_seq.reshape(1, seq_length, 1))
    predictions.append(pred[0][0])
    current_seq = np.append(current_seq[1:], pred, axis=0)

# Inverse transform the predictions
predictions = scaler.inverse_transform(np.array(predictions).reshape(-1, 1))

# Prepare the results for saving
forecast_weeks = list(range(31, 44))
forecast_results = pd.DataFrame({"Week": forecast_weeks, "Forecasted Net Sales": predictions.flatten()})

# Save the results to a CSV file
forecast_results.to_csv("forecast_results.csv", index=False)

# Plotting the data
plt.figure(figsize=(12, 6))
plt.plot(df['Week'], df['Net Sales'], label='Historical Data', color='blue')
plt.plot(forecast_results['Week'], forecast_results['Forecasted Net Sales'], label='Forecasted Data', color='red')
plt.axvline(x=30, linestyle='--', color='gray', label='Forecast Start')
plt.xlabel('Week')
plt.ylabel('Net Sales')
plt.title('Net Sales Forecast')
plt.legend()
plt.show()
```

```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Dense, LSTM, Dropout
import matplotlib.pyplot as plt

# Manually create the dataset from the given data
data = {
    "Week": list(range(1, 44)),
    "Net Sales": [158, 97, 111, 33, 86, 74, 43, 125, 90, 102, 80, 64, 62, 74, 75, 82, 80, 75, 70, 90, 71, 14, 68, 39, 72, 64, 74, 88, 88, 126, 84, 67
}

# Create a DataFrame
df = pd.DataFrame(data)

# Use the first 30 weeks for training
train_data = df[df['Week'] <= 30]['Net Sales'].values.reshape(-1, 1)
test_data = df[df['Week'] > 30]['Net Sales'].values.reshape(-1, 1)

# Normalize the data
scaler = MinMaxScaler()
train_data_scaled = scaler.fit_transform(train_data)
test_data_scaled = scaler.transform(test_data)

# Create training sequences
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i + seq_length])
        y.append(data[i + seq_length])
    return np.array(X), np.array(y)

seq_length = 10  # using a longer sequence length
X_train, y_train = create_sequences(train_data_scaled, seq_length)
X_test, y_test = create_sequences(test_data_scaled, seq_length)
```

Appendix B – Exponential Smoothing Forecasting Using Excel

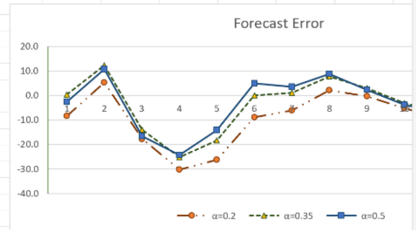


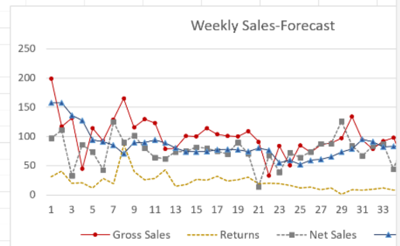
	Store 20		Store 15		Store21		Store 28	
	Sales	Returns	Sales	Returns	Sales	Returns	Sales	Returns
Row Labels	سوبر ماركت ساريس		سوبرماركت ال 4 cats		سوبرماركت سارة 2		عمراوة	
1	7	2	14	0	7	1	6	1
2	4	1	9	2	5	0	5	1
3	4	0	8	1	7	0	8	1
4	0	1	0	4	2	1	7	0
5	5	0	6	3	6	0	7	2
6	5	0	5	0	7	0	3	0
7	10	1	4	1	10	0	6	0
8	6	6	5	3	8	4	7	8
9	10	6	7	0	12	0	5	2
10	8	0	4	1	9	0	5	2
11	7	0	4	0	8	2	8	1
12	4	4	3	0	2	1	4	3
13	2	0	2	1	5	0	5	2
14	8	2	7	5	1	0	7	1
15	6	0	9	1	2	0	5	1
16	3	0	3	2	7	0	8	5
17	4	3	6	0	3	0	5	2
18	8	4	5	3	7	0	7	6
19	7	0	8	2	2	3	13	3
20	8	2	6	7	5	0	5	7
21	8	1	3	1	6	0	6	2
22	3	1	6	2	0		3	0
23	8	2	5	2	3	0	3	3
24	6	1	4	3	0	1	7	2
25	3	0	4	0	3	0	2	3
26	8	0	2	0	6	0	0	0
27	6	0	4	1	3	0	5	0
28	5	0	4	0	3	3	6	2
29	8	0	5	0	4	0	9	0
30	9	0	8	0	4	0	5	0
31	8	0	5	0	0	0	3	0
32	6	0	4	0	0	0	7	0
33	10	0	3	0	2	0	3	0
34	5	0	4	0	2	0	7	0
35	7	0	2	0	2	0	2	0
36	17	0	6	0	4	0	4	0
37	4	0	4	0	6	0	6	3
38	11	2	6	0	0	0	2	1
39	5	0	4	0	6	0	3	0
40	5	1	4	1	0	0	4	1
41	4	0	5	0	6	0	7	0
42	5	0	7	1	2	0	6	0
43			3	0	1	0	7	1
44			0					
Grand Tota	1283	267	217	178	233	234		



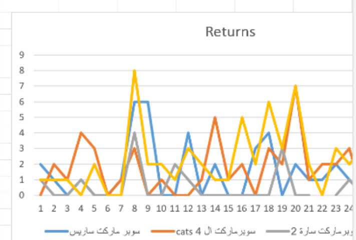
	Column Labels									
	سوبر ماركت ساريس		سوبرماركت ال 4 cats		سوبرماركت سارة 2		عمراوة		Total Sum of Sales	Total Sum of Returns
Row Labels	Sum of Sales	Sum of Returns	Sum of Sales	Sum of Returns	Sum of Sales	Sum of Returns	Sum of Sales	Sum of Returns		
1	7	2	14	0	7	1	6	1	34	4
2	4	1	9	2	5	0	5	1	23	4
3	4	0	8	1	7	0	8	1	27	2
4	0	1	0	4	2	1	7	0	9	6
5	5	0	6	3	6	0	7	2	24	5
6	5	0	5	0	7	0	3	0	20	0
7	10	1	4	1	10	0	6	0	30	2
8	6	6	5	3	8	4	7	8	26	21
9	10	6	7	0	12	0	5	2	34	8
10	8	0	4	1	9	0	5	2	26	3
11	7	0	4	0	8	2	8	1	27	3
12	4	4	3	0	2	1	4	3	13	8
13	2	0	2	1	5	0	5	2	14	3
14	8	2	7	5	1	0	7	1	23	8
15	6	0	9	1	2	0	5	1	22	2
16	3	0	3	2	7	0	8	5	21	7
17	4	3	6	0	3	0	5	2	18	5
18	8	4	5	3	7	0	7	6	27	13
19	7	0	8	2	2	3	13	3	30	8
20	8	2	6	7	5	0	5	7	24	16
21	8	1	3	1	6	0	6	2	23	4
22	3	1	6	2			3	0	12	3
23	8	2	5	2	3	0	3	3	19	7
24	6	1	4	3	0	1	7	2	17	7
25	3	0	4	0	3	0	2	3	12	3
26	8	0	2	0	6	0			16	0
27	6	0	4	1	3	0	5	0	18	1
28	5	0	4	0	3	3	6	2	18	5
29	8	0	5	0	4	0	9	0	26	0
30	9	0	8	0	4	0	5	0	26	0
31	8	0	5	0			3	0	16	0
32	6	0	4	0			7	0	17	0
33	10	0	3	0	2	0	3	0	18	0
34	5	0	4	0	2	0	7	0	18	0
35	7	0	2	0	2	0	2	0	13	0
36	17	0	6	0	4	0	4	0	31	0
37	4	0	4	0	6	0	6	3	20	3
38	11	2	6	0			2	1	19	3
39	5	0	4	0	6	0	3	0	18	0

					α=0.2		α=0.35		α=0.5
				α=	0.2	α=	0.35	α=	0.5
Week	Gross Sales	Returns	Net Sales	Forecast	error	Forecast	error	Forecast	error
1	199	31	158	158.0	**0.0**	158.0	**0.0**	158.0	**0.0**
2	117	41	97	158.0	**-61.0**	158.0	**-61.0**	158.0	**-61.0**
3	132	20	111	145.8	**-34.8**	136.7	**-25.7**	127.5	**-16.5**
4	45	21	33	138.8	**-105.8**	127.7	**-94.7**	119.3	**-86.3**
5	114	12	86	117.7	**-31.7**	94.5	**-8.5**	76.1	**9.9**
6	93	28	74	111.3	**-37.3**	91.5	**-17.5**	81.1	**-7.1**
7	129	19	43	103.9	**-60.9**	85.4	**-42.4**	77.5	**-34.5**
8	165	86	125	91.7	**33.3**	70.6	**54.4**	60.3	**64.7**
9	116	40	90	98.4	**-8.4**	89.6	**0.4**	92.6	**-2.6**
10	130	26	102	96.7	**5.3**	89.8	**12.2**	91.3	**10.7**
11	123	28	80	97.7	**-17.7**	94.0	**-14.0**	96.7	**-16.7**
12	79	43	64	94.2	**-30.2**	89.1	**-25.1**	88.3	**-24.3**
13	80	15	62	88.2	**-26.2**	80.3	**-18.3**	76.2	**-14.2**
14	101	18	74	82.9	**-8.9**	73.9	**0.1**	69.1	**4.9**
15	100	27	75	81.1	**-6.1**	73.9	**1.1**	71.5	**3.5**
16	114	25	82	79.9	**2.1**	74.3	**7.7**	73.3	**8.7**
17	104	32	80	80.3	**-0.3**	77.0	**3.0**	77.6	**2.4**
18	101	24	75	80.3	**-5.3**	78.1	**-3.1**	78.8	**-3.8**
19	100	26	70	79.2	**-9.2**	77.0	**-7.0**	76.9	**-6.9**
20	109	30	90	77.4	**12.6**	74.5	**15.5**	73.5	**16.5**
21	91	19	71	79.9	**-8.9**	80.0	**-9.0**	81.7	**-10.7**
22	33	20	14	78.1	**-64.1**	76.8	**-62.8**	76.4	**-62.4**
23	84	19	68	65.3	**2.7**	54.8	**13.2**	45.2	**22.8**
24	51	16	39	65.8	**-26.8**	59.4	**-20.4**	56.6	**-17.6**
25	85	12	72	60.5	**11.5**	52.3	**19.7**	47.8	**24.2**
26	73	13	64	62.8	**1.2**	59.2	**4.8**	59.9	**4.1**
27	86	9	74	63.0	**11.0**	60.9	**13.1**	61.9	**12.1**
28	89		88	65.2	**22.8**	65.5	**22.5**	68.0	**20.0**
29	97	1	88	69.8	**18.2**	73.4	**14.6**	78.0	**10.0**
30	134	9	126	73.4	**52.6**	78.5	**47.5**	83.0	**43.0**
31	94	8	84	83.9	**0.1**	95.1	**-11.1**	104.5	**-20.5**
32	79	10	67	83.9	**-16.9**	91.2	**-24.2**	94.2	**-27.2**
33	92	12	84	80.6	**3.4**	82.7	**1.3**	80.6	**3.4**
34	98	8	88	81.2	**6.8**	83.2	**4.8**	82.3	**5.7**
35	53	10	44	82.6	**-38.6**	84.9	**-40.9**	85.2	**-41.2**
36	123	9	96	74.9	**21.1**	70.6	**25.4**	64.6	**31.4**
37	112	27	98	79.1	**18.9**	79.5	**18.5**	80.3	**17.7**
38	96	14	82	82.9	**-0.9**	86.0	**-4.0**	89.1	**-7.1**
39	83	14	65	82.7	**-17.7**	84.6	**-19.6**	85.6	**-20.6**
40	41	18	30	79.2	**-49.2**	77.7	**-47.7**	75.3	**-45.3**





	Sum of Sales				**Sum of Returns**				**Total Sum**	**Total Sum of Returns**
Row Labels	**سوبر ماركت ساريس**	**cats 4 سوبرماركت ال**	**2 سوبرماركت سارة**	**عمراوة**	**سوبر ماركت ساريس**	**cats 4 سوبرماركت ال**	**2 سوبرماركت سارة**	**عمراوة**		
1	7	14	7	6	2	0	1	1	34	4
2	4	9	5	5	1	2	0	1	23	4
3	4	8	7	8	0	1	0	1	27	2
4	0	0	2	7	1	4	1	0	9	6
5	5	6	6	7	0	3	0	2	24	5
6	5	5	7	3	0	0	0	0	20	0
7	10	4	10	6	1	1	0	0	30	2
8	6	5	8	7	6	3	4	8	26	21
9	10	7	12	5	6	0	0	2	34	8
10	8	4	9	5	0	1	0	2	26	3
11	7	4	8	8	0	0	2	1	27	3
12	4	3	2	4	4	0	1	3	13	8
13	2	2	5	5	0	1	0	2	14	3
14	8	7	1	7	2	5	0	1	23	8
15	6	9	2	5	0	1	0	1	22	2
16	3	3	7	8	0	2	0	5	21	7
17	4	6	3	5	3	0	0	2	18	5
18	8	5	7	7	4	3	0	6	27	13
19	7	8	2	13	0	2	3	3	30	8
20	8	6	5	5	2	7	0	7	24	16
21	8	3	6	6	1	1	0	2	23	4
22	3	6		3	1	2		0	12	3
23	8	5	3	3	2	2	0	3	19	7
24	6	4	0	7	1	3	1	2	17	7
25	3	4	3	2	0	0	0	3	12	3
26	8	2	6		0	0	0		16	0
27	6	4	3	5	0	1	0	0	18	1
28	5	4	3	6	0	0	3	2	18	5
29	8	5	4	9	0	0	0	0	26	0
30	9	8	4	5	0	0	0	0	26	0
31	8	5		3	0	0		0	16	0
32	6	4		7	0	0		0	17	0
33	10	3	2	3	0	0	0	0	18	0
34	5	4	2	7	0	0	0	0	18	0
35	7	2	2	2	0	0	0	0	13	0
36	17	6	4	4	0	0	0	0	31	0
37	4	4	6	6	0	0	0	3	20	3
38	11	6		2	2	0		1	19	3
39	5	4	6	3	0	0	0	0	18	0
40	5	4		4	1	1		1	13	3
41	4	5	6	7	0	0	0	0	22	0



A449 | 4/26/2017

	TransactionDat	Week	MONTI	weekda	ItemCoc	ItemName	Sales	Return	Forecastin	RouteCod	CustomerName
2	1/1/2017	1	1	1	9001	3% Milk FF 1L	10	0		N - 301	سوبر ماركت الكواليس
3	1/2/2017	1	1	2	9001	3% Milk FF 1L	0	1		N - 301	سوبر ماركت الكواليس
4	1/2/2017	1	1	2	9001	3% Milk FF 1L	4	0		N - 301	سوبر ماركت ساريس
5	1/2/2017	1	1	2	9001	3% Milk FF 1L	2	0		N - 301	المنهل ستورز
6	1/2/2017	1	1	2	9001	3% Milk FF 1L	6	0		N - 301	سوبرماركت ال 4 cats
7	1/2/2017	1	1	2	9001	3% Milk FF 1L	6	0		N - 301	مخزن التوقف و التسوق
8	1/2/2017	1	1	2	9001	3% Milk FF 1L	2	0		N - 301	زيد الكساسبة
9	1/2/2017	1	1	2	9001	3% Milk FF 1L	2	0		N - 301	سوبر ماركت محمد و هاشم بدوان
10	1/3/2017	1	1	3	9001	3% Milk FF 1L	0	2		N - 301	حارتنا
11	1/3/2017	1	1	3	9001	3% Milk FF 1L	2	0		N - 301	سوبرماركت مثلث الجبيهه
12	1/3/2017	1	1	3	9001	3% Milk FF 1L	15	0		N - 301	سوبر ماركت الكواليس
13	1/4/2017	1	1	4	9001	3% Milk FF 1L	3	2		N - 301	سوبر ماركت ساريس
14	1/4/2017	1	1	4	9001	3% Milk FF 1L	6	0		N - 301	سوبر ماركت أسكادنيا
15	1/4/2017	1	1	4	9001	3% Milk FF 1L	2	0		N - 301	المنهل ستورز
16	1/4/2017	1	1	4	9001	3% Milk FF 1L	8	0		N - 301	سوبرماركت ال 4 cats
17	1/4/2017	1	1	4	9001	3% Milk FF 1L	3	0		N - 301	سوبرماركت الأحفاد
18	1/4/2017	1	1	4	9001	3% Milk FF 1L	1	0		N - 301	سوبرماركت السطري
19	1/4/2017	1	1	4	9001	3% Milk FF 1L	3	0		N - 301	سوق وسام المركزي
20	1/4/2017	1	1	4	9001	3% Milk FF 1L	2	2		N - 301	أسواق الماضي
21	1/4/2017	1	1	4	9001	3% Milk FF 1L	4	0		N - 301	أسواق الشاهر
22	1/4/2017	1	1	4	9001	3% Milk FF 1L	3	0		N - 301	حارتنا
23	1/4/2017	1	1	4	9001	3% Milk FF 1L	4	0		N - 301	سوبر ماركت عبد الناصر
24	1/4/2017	1	1	4	9001	3% Milk FF 1L	6	0		N - 301	مخزن التوقف و التسوق
25	1/4/2017	1	1	4	9001	3% Milk FF 1L	2	0		N - 301	سائد مول
26	1/5/2017	1	1	5	9001	3% Milk FF 1L	1	0		N - 301	المنسي
27	1/5/2017	1	1	5	9001	3% Milk FF 1L	0	2		N - 301	لذة اسطنبول
28	1/5/2017	1	1	5	9001	3% Milk FF 1L	4	0		N - 301	زيد الكساسبة
29	1/5/2017	1	1	5	9001	3% Milk FF 1L	3	0		N - 301	وليد عوض
30	1/5/2017	1	1	5	9001	3% Milk FF 1L	2	0		N - 301	سوبرماركت مثلث الجبيهه
31	1/7/2017	1	1	7	9001	3% Milk FF 1L	0	3		N - 301	سوبرماركت الأحفاد
32	1/8/2017	2	1	1	9001	3% Milk FF 1L	10	0		N - 301	سوبر ماركت الكواليس
33	1/8/2017	2	1	1	9001	3% Milk F Chart Area	2	0		N - 301	سوبر ماركت محمد و هاشم بدوان
34	1/9/2017	2	1	2	9001	3% Milk FF 1L	4	0		N - 301	سوبر ماركت محمد و هاشم بدوان
35	1/9/2017	2	1	2	9001	3% Milk FF 1L	1	1		N - 301	سوبر ماركت عبد الناصر
36	1/9/2017	2	1	2	9001	3% Milk FF 1L	2	0		N - 301	زيد الكساسبة
37	1/9/2017	2	1	2	9001	3% Milk FF 1L	4	0		N - 301	مخزن التوقف و التسوق
38	1/9/2017	2	1	2	9001	3% Milk FF 1L	6	0		N - 301	سوبر ماركت الكواليس
39	1/9/2017	2	1	2	9001	3% Milk FF 1L	2	0		N - 301	سوبر ماركت ساريس
40	1/9/2017	2	1	2	9001	3% Milk FF 1L	4	0		N - 301	سوبر ماركت أسكادنيا
41	1/9/2017	2	1	2	9001	3% Milk FF 1L	4	1		N - 301	سوبرماركت ال 4 cats
42	1/9/2017	2	1	2	9001	3% Milk FF 1L	1	1		N - 301	أسواق الجزيره للتموين
43	1/9/2017	2	1	2	9001	3% Milk FF 1L	0	2		N - 301	أسواق الماضي
44	1/9/2017	2	1	2	9001	3% Milk FF 1L	0	1		N - 301	أسواق الشاهر

Pivot | Forecat | Sheet1 | Sales per store | Sheet3 | N 301 & 301A