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Developing AI-Powered Demand Forecasting Models with .NET for Shipping and Furniture Industries

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ABSTRACT

Demand forecasting is imperative in industries like shipping and furniture, where structured supply chain management is required to ensure optimized inventory and customer satisfaction. This paper looks into developing AI-powered demand forecasting models with .NET for the shipping and furniture industries. This paper also delves deeper into how machine learning can be used to accurately and effectively predict future demand trends. This paper will discuss several processes, such as data collection and evaluation of machine learning models that can be used in forecasting future trends. This paper will examine how this AI-powered model will be integrated with .NET frameworks to ensure optimization. Case studies will be discussed to highlight the challenges experienced and the solutions to the problems. The integration of this system with other real-world businesses will be discussed. Lastly, the paper will discuss the challenges, lessons learned, and future work.

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Introduction

Demand forecasting is crucial and imperative in supply chain management in industries like shipping and furniture, where predicting future market trends is crucial. Such industries need accurate and reliable demand forecasting to optimize inventory levels, minimize stockout and overstock, minimize holding costs, and ensure their systems run efficiently. Demand forecasting is essential in the shipping and furniture industry because the supply chain affects the customer experience, which corresponds to the profitability of the companies in this industry [1]. Demand forecasting has been made more efficient with Artificial Intelligence (AI) and Machine Learning (ML). Past forecasting techniques have been proven insufficient in accurately predicting demand because they cannot analyze complex data, which is essential in accurate demand forecasting. ML and AI will effectively predict demand because they can analyze complex data and determine relationships between data to ensure accurate information.

There are a variety of challenges faced in the shipping and furniture industry, one of them being demand forecasting because the available methods for predicting the demand are insufficient to produce accurate and reliable information about the demand. This problem is usually faced because economic factors, seasons, trends, and ever-changing customer preferences cause many demand fluctuations. The available traditional methods can analyze such factors to predict the demand. Therefore, the shipping and furniture industry needs more sophisticated algorithms to handle such complex data, analyze it, and predict future demand, which is accurate to increase reliability [2].

The primary goal of this paper is to look into the strategies and processes that will be applied in developing AI-powered demand forecasting models using .NET frameworks for shipping and furniture industries and using machine learning to increase the accuracy of these models. Real-world systems in the shipping and furniture industries will use this AI model for demand forecasting, providing benefits to companies such as increased revenue, minimized production and operation costs, and increased customer satisfaction. This paper delved deeper into the efficient ways of developing AI models for demand forecasting in the highlighted industries.

Background and Literature Review

Importance of Demand Forecasting

Demand forecasting is essential in supply chain management because it helps minimize holding costs, maximize profit, and improve customer experience in the supply and furniture industries. In the shipping industry, there are many fluctuations in the market due to various factors that can affect the demand for shipping services; therefore, accurate demand forecasting helps ensure these fluctuations do not hurt the shipping companies' logistics, transportation, and warehousing. Demand forecasting is essential in companies dealing with furniture because this industry is greatly affected by trends and economic factors [3]. This industry needs demand forecasting to implement efficient strategies so that furniture production is efficient and warehouse spaces can be used and optimized.

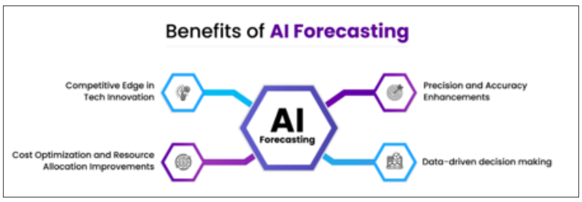

Figure 1: Shows the Benefits of AI Forecasting

Literature Review on AI and Machine Learning

In recent years, AI and ML have been integrated into real-world businesses and have shown significant improvement in demand forecasting accuracy. This is because AI and ML can process complex and nonlinear data that previous traditional methods could not handle. Machine learning techniques such as decision trees and neural networks can be applied to AI-powered models because they have been tested and proven to increase demand forecasting accuracy. These techniques analyze data such as trends, seasons, customer preferences, and economic indicators to come up with accurate information that will be used for demand forecasting. Time series forecasting methodologies like AutoRegressive Integrated Moving Average (ARIMA) have been tested before and shown to help increase the accuracy of demand forecasting models [4].

Characteristics	Models	ARIMA (1, 0, 2)	ARIMA (2, 0, 2)	ARIMA (1, 0, 1)	ARIMA (1, 0, 0)	ARIMA (0, 0, 1)	ARIMA (1, 0, 1) without constant
AR (1)	α_1	0.92913	0.71371	0.90792	0.49434	−0.41704	0.99755623
	SEB	0.104616	0.761758	0.094852	0.1074471	0.1119989	0.00444769
	T value	8.8813204	0.9369292	9.571955	4.600820	−3.723567	224.28617
	p Value	0.00000000	0.35216008	0.00000000	0.00001823	0.00039384	0.0000000
MA (1)	θ_1	0.52269	0.31779	0.63880			0.71392452
	SEB	0.167073	0.741595	0.161531			0.08579173
	T value	3.1284995	0.4285186	3.954655			8.32160
	p Value	0.00258711	0.66964815	0.00018319			0.0000000
AR (2)	α_2		0.19759				
	SEB		0.659442				
	T value		0.2996279				
	p Value		0.76538859				
MA (2)	θ_2	0.17062	0.30202				
	SEB	0.142258	0.409353				
	T value	1.1993429	0.7377864				
	p Value	0.23455708	0.46322050				
Constant	Cte	124.42969	124.52640	125.53260	128.53887	129.22650	
	SEB	12.608189	12.601296	11.785537	6.5715235	4.8971088	
	T value	9.8689581	9.8820312	10.651411	19.559981	26.388326	
	p Value	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	
AIC		688.86593	690.82312	688.77347	689.37103	693.59055	692.04831
SBC		697.9726	702.20645	695.60347	693.92437	698.14388	696.60164
Log likelihood		−340.43297	−340.41156	−341.38674	−342.68552	−344.79527	−344.02415
Error		28.034898	28.221721	28.214812	28.576249	29.443759	28.461048

SBC: Schwarz Bayesian criterion; AIC: Akaike criterion; ARIMA: autoregressive integrated moving average; SEB: Standard Error of B (B: Regression Coefficient).

Figure 2: Shows the Accuracy of Different ARIMA Models in Demand Forecasting

Model Development

Model Selection

Different AI models are used to perform different functions; in this case, this study mainly focuses on the AI models suitable for performing demand forecasting functions. The following factors should be considered when selecting an AI model for demand forecasting:

- **The Characteristics of the Data the Model is Intended to Receive:** The AI model will receive complex data about past demand trends, the nature of the market and seasons, and current customer preferences. This data is usually complex and non-linear, so the developer should ensure the AI model chosen can manipulate such data.
- **Interpretation:** Different interpretations are applied depending on the complexity of the data. The most common types of interpretation are neural networks, decision trees, and linear regression. In this case, neural networks will be most efficient because they can process the complex data that is meant to be used for demand forecasting [5].

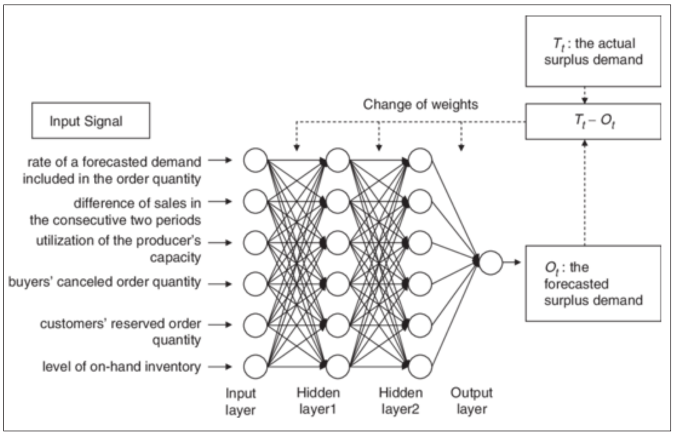

Figure 3: Shows the Diagrammatical Representation of Neural Networks

- **Performance:** This criterion is paramount when selecting the AI model for demand forecasting. This means that the model should be able to accept data, process it, and procure accurate results within the specified time frame. The model should also perform as intended, even when there are large volumes of data. Therefore, the system should be highly scalable.
- **Model Complexity:** There are two factors in this sector; the first is overfitting, whereby an AI model can be trained using various types of data in nature and complexity. However, the model might provide unreliable and inaccurate information when data of other nature is fed into it, and the data may need to be simplified or familiar for the model to process. The second factor here is underfitting, whereby an AI model can be trained to perform functions such as demand forecasting and will fail in performing its tasks because it needs to capture more background information, which is imperative when making deductions about demand forecasting.

ML.NET Models

Linear Regression is a simple algorithm used to analyze linear data, which is very simple and easily predictable. It is usually fast and accurate only when processing linear data. This algorithm cannot be used when processing complex, non-linear data like the ones used for demand forecasting.

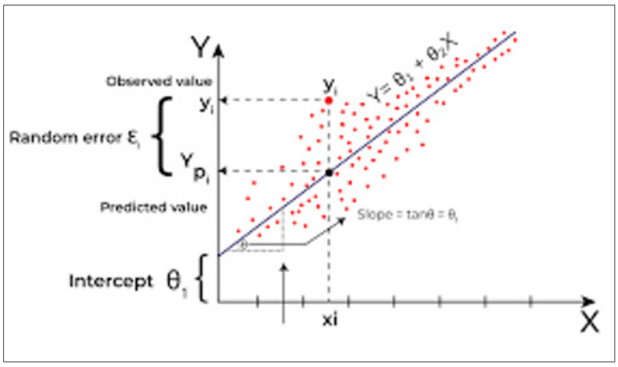

Figure 4: Shows Linear Regression

Decision Trees

This algorithm was previously used by AI models to perform complex functions such as analyzing nonlinear data. In the past few years, however, it was seen that this algorithm was producing inaccurate results, so other more sophisticated mechanisms were employed.

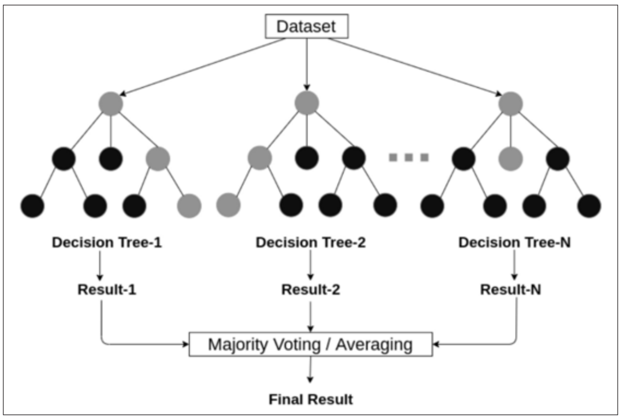

Figure 5: Shows Decision Trees

Neural Networks are an algorithm most suitable for handling complex nonlinear data in demand forecasting. It can determine the relationships between different datasets and produce accurate predictions. However, this algorithm is very complex to construct [6].

Model Training

Data Splitting: Data is split to determine the data used in training and testing the AI-powered model. A common slit used is the 80/20 ratio, which means that 80% of the data will be used for training, and 20% of the data will be used for training [7].

```
// Splitting data into training and testing sets using ML.NET
var partitions = mlContext.Data.TrainTestSplit(data, testFraction: 0.2);
var trainData = partitions.TrainSet;
var testData = partitions.TestSet;
```

Figure 6: Shows a Short Code Snippet of Data Splitting

Training Algorithms: ML.NET supports a variety of training algorithms for demand forecasting, one of them being the regression model.

```
// Define the learning pipeline for a regression model
var pipeline = mlContext.Transforms.Concatenate("Features",
                new[] { "Lag1Sales", "Lag2Sales", "MovingAvgSales", "IsHoliday", "Temperature" })
               .Append(mlContext.Transforms.NormalizeMinMax("Features"))
               .Append(mlContext.Regression.Trainers.Sdca(labelColumnName: "Label", featureColumnName: "Features"));

// Train the model
var model = pipeline.Fit(trainData);
```

Figure 7: Shows A Code Snippet of Training an Algorithm

Figure showing an example of code snippet of training a regression model

Hyperparameter Tuning: ML.NET provides the grid search tool, which is crucial in improving the performance of the demand forecasting AI-powered model.

```
// Example of hyperparameter tuning using ML.NET's AutoML
var experimentSettings = new RegressionExperimentSettings { MaxExperimentTimeInSeconds = 600 };
var experiment = mlContext.Auto().CreateRegressionExperiment(experimentSettings);

var result = experiment.Execute(trainData, labelColumnName: "Label");
var bestModel = result.BestRun.Model;
```

Figure 8: Shows a Code Snippet of Hyperparameter Tuning

Model Assessment

After training the AI-powered model, evaluation is done to determine if it will produce accurate results. The following highlights the metrics in assessing the performance of demand forecasting AI models:

Mean Absolute Error (MAE)

Determines the error magnitude produced in the demand forecasting model.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Figure 9: Shows the MAE Formula

Figure showing the formula for calculating MAE

R-Squared (R^2) shows the magnitude of the variance between the dependent and independent variables. The result range is usually 0 to 1; a higher index indicates better performance.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Figure 10: Shows the R-squared Formula

Mean Squared Error (MSE) indicates the squared errors of AI models.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Figure 11: Shows the MSE Formula

Root Mean Squared Error (RMSE)

Shows the average magnitude of an error.

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$$

Figure 12: Shows the RMSE Formula

Implementation of the AI-Powered Demand Forecasting Model with .NET

Development Environment

The following needs to be done to set up a development environment for creating the AI model.

- **Install Visual Studio Code:** This IDE supports development using .NET frameworks such as ML.NET and C# [8].
- **Install ML.NET:** This framework allows the development of AI-powered models that use .NET frameworks.
- **.NET Frameworks:** This is a library that enables one to develop applications using .NET

Code Implementation

- **Data Loading:** The model loads data such as seasons, trends, economic factors, customer preferences, and past sales data to determine future demands.
- **Feature Engineering:** Generate features that are suitable for the data entered
- **Model Training:** Train the model using various datasets to ensure it can produce accurate and reliable data.
- **Model Evaluation:** Different mechanisms, such as MAE, MSE, etc., are employed to determine the model's performance.

```
using Microsoft.ML;
using Microsoft.ML.Data;

public class SalesData
{
    [LoadColumn(0)]
    public float Sales { get; set; }

    [LoadColumn(1)]
    public float Lag1Sales { get; set; }

    [LoadColumn(2)]
    public float Temperature { get; set; }

    [LoadColumn(3)]
    public bool IsHoliday { get; set; }

    // Additional columns as needed
}

var mlContext = new MLContext();
IDataView dataView = mlContext.Data.LoadFromTextFile<SalesData>("data/sales.csv", separatorChar: ',', hasHeader: true);
```

Figure 13: Shows an Example of a Code Snippet on Data Loading

Case Studies

Maersk Shipping Company

Maersk Shipping Company is the second-largest shipping company in the world. It was founded in 1904 by Arnold Peter Moller, who was Danish. The company makes an annual revenue of over US$51 billion from shipping services to 374 ports in 116 countries worldwide. Maersk experiences several challenges in determining the demand for shipping services worldwide. Seasonal variation greatly affected the demand for shipping services, whereby there was high demand during seasons such as Christmas and seasons when the demand was low. Operational costs of their vessels and port fees also played a role in fluctuating demand for shipping services. The available techniques used in demand forecasting needed to be more sufficient to predict future demands for shipping services accurately.

To solve the demand prediction problem, AI-powered applications using Microsoft's .NET framework were implemented to predict the demand for shipment services accurately. AI increased the accuracy of future demand predictions by up to 20%. The Generative AI allows one to enter comprehensive data about previous sales, shipping routes, shipping schedules, and information such as factors causing fluctuations in demand to determine reliable demand predictions. Generative AI significantly helped reduce operational costs and ensure automated supply chain management, inventory management, and demand forecasting. After the implementation of Generative AI, Maersk made a revenue of US$62 billion profit in the year 2022.

Highlights for the year — USD million

	Revenue		EBITDA		EBIT		CAPEX	
	2021	2020	2021	2020	2021	2020	2021	2020
Ocean	48,232	29,175	21,432	6,545	17,963	3,196	2,003	609
Logistics & Services	9,830	6,963	907	454	623	264	460	153
Terminals & Towage	4,715	3,807	1,675	1,205	1,294	828	454	457
Manufacturing & Others	1,348	1,254	136	165	-103	69	53	33
Unallocated activities, eliminations, etc.	-2,338	-1,459	-114	-143	-103	-171	6	70
A.P. Moller - Maersk consolidated	**61,787**	**39,740**	**24,036**	**8,226**	**19,674**	**4,186**	**2,976**	**1,322**

Figure 14: Shows Revenue for Maersk in 2022

Model Integration with Business Systems

The AI-powered demand forecasting model can be integrated into real-world business to predict future demand. The model should be connected to data sources that provide real-time data about relevant data that will be used in the predictions. In this case, the sources can be ERP systems, which provide comprehensive data about a company's sales. The model needs to have accurate real-time data to produce accurate results. The model should provide dashboards and reports for the predictions, whereby the dashboard will provide the company managers with a simplified format of the predictions, which are easy to understand [9]. The model generates regular reports periodically to provide information about the demand information and insights about the model's performance. The model should provide real-time forecasting to provide reliable company operations data.

Challenges, Limitations and Lessons Learnt

Technical challenges

There are a variety of technical challenges that could be faced in the development of AI-powered demand forecasting models with .NET for furniture and shipping companies. One of the challenges is the complexity of the development of the models. Algorithms such as neural models are complex to develop because they require a lot of training and hyperparameter training to ensure the model is performing efficiently; such a process is very time consuming and expensive as it requires a lot of resources to develop.

Integrating AI models into existing systems is often challenging because problems such as system incompatibility may be encountered. Integrating an AI model that is not fully compatible with a particular system will eventually cause a system breakdown, which is time-consuming and costly. The scalability of the existing system needs to be evaluated before integrating an AI model to ensure that it can process large volumes of data and that the system is running smoothly.

Limitations

As much as AI models provide valuable insights about demand forecasting, the information is only partially reliable because it may contain errors, or market trends could change drastically, rendering the information invaluable. The model could also provide information that is hard to understand, leading to misinterpretations by company managers and, therefore, the wrong conclusions.

This study has limitations. It provides case studies that may only partially apply to using AI-powered models in demand forecasting in the shipping and furniture industry. Studies conducted about this sector may not have been done in optimal environments, where time and resources may have been insufficient to produce the results.

Future Work

Modern technology, such as explainable AI (XAI), will help explain complex reports the AI model uses. This feature will be essential to stakeholders because they will have detailed instructions on getting optimized demand forecasting information. Integrating real-time data processing information is essential to ensure timely demand prediction.

Conclusion

This paper provides an in-depth highlight of developing an AI-powered demand forecasting model with .NET for the shipping and furniture industries. This paper provides a literature review of previous research on this topic and why AI-powered models should be used in demand forecasting in the shipping and furniture industries. It then provides details about various data collection sources and how the data is prepared to be used by the mode. The criteria required for model development are analyzed, showcasing the training and evaluation methods of the AI models. Implementation of the AI model with .NET has been discussed to show the environments needed for development. Maersk Shipping Company has been discussed to show how AI models have been used to ease the process of demand forecasting while increasing revenue. The challenges, limitations, and future work have been discussed in this paper. AI models have shown that there will be significant changes with the transition from the traditional methods of demand forecasting to the modern methods; there will be increased sales, minimum operations cost, and improved customer experience [10,11].

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