Deep Learning in Fashion and Apparel Retail Industry

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Compared to other industries, fashion apparel retail faces many challenges in predicting future demand for its products with a high degree of precision. Fashion products' short life cycle, insufficient historical information, highly uncertain market demand, and periodic seasonal trends necessitate the use of models that can contribute to the efficient forecasting of products' sales and demand. Many researchers have tried to address this problem using conventional forecasting models that predict future demands using historical sales information. Machine learning and deep learning models such as the support vector machine, neural network, and recurrent neural network are among many forecast models that have gained popularity among forecast researchers and practitioners given their ability to overcome the drawbacks of traditional linear forecast models.

Keywords: sales forecasting ; deep learning ; fashion and apparel industry ; machine learning

1. Introduction

Given the growing number of fashion e-commerce digital platforms, customers can see and choose from a massive number of virtual fashion products merchandised virtually. There has been a dramatic shift in customers' purchasing behaviour, which is impacted by several factors, such as social media, fashion events, and so forth. Consumers now increasingly prefer to select their products from the immense pool of options and want them to be delivered in a very short time. It is challenging for fashion retailers to fulfil consumer demands in a short time interval [1]. Therefore, it is crucial for fashion apparel retailers to make efficient and quick decisions concerning inventory replenishment in advance based on the forecast of future demand patterns.

Demand forecasting plays a crucial role in managing efficient supply chain operations in the fashion retail industry. Poor forecasting models lead to inefficient management of the stock inventory, obsolescence, and disorderly resource utilisation across the upstream supply chain. Usually, profit-oriented companies are much more concerned about forecasting models as most of their business decisions are made based on the predicted future uncertainties related to product demand and sales. In the fashion apparel industry, a plethora of factors such as different product styles, patterns, designs, short life cycles, fluctuating demands, and extended replenishment lead times lead to flawed or less accurate predictions of future product demand or sales [2][3]. The apparel fashion industry is attempting to develop robust forecast models, which can help improve the overall efficiency in the decision-making related to sourcing as well as sales.

Most of the existing research on fashion supply chain management is devoted to developing advanced models for improving the forecast of demand for fashion apparel items [4][5]. Accurately predicting future sales and demand for fashion products remains a central problem in both industry and academia. To address this challenge, it is imperative to study the complexity of the fashion market and managerial strategies that would allow products to be designed, produced, and delivered on time [6]. The fashion apparel industry has been undergoing significant transitions given factors such as dynamic pricing strategies, inventory management, globalisation, and consumer-centric and technology-oriented product design and manufacturing. In need to overcome complexities arising out of these factors, the fashion industry strives to manage these rapid changes more effectively by adopting an agile supply chain [7][8].

The frequency at which new fashion product arrives in the market is relatively very high. How these new fashion products will spare in the market in terms of sales and demand is often the main focus of decision-makers in the fashion supply chain [9]. Therefore, it becomes a difficult challenge for the fashion retailers to predict the future demand and sale of a newly arrived fashion product amidst various factors such as changing consumer choices, in numerous product types, instability in the market, uncertainty in the supply chain, and poor predictability by week or item. In the era of big data, the fashion apparel retail industry produces a considerable amount of sales and item-related information [10] and, if this is handled effectively using cutting-edge data analytics tools, business performance in the fashion industry could be significantly improved.

In fashion retail management, forecast models for predicting product sales and demand are traditionally applied to historical product data that contains sales information and image data features [9]. However, there is often a lack of historical data for the newly arriving fashion item. In the absence of historical data, predicting future demand and sale of a newly arrived fashion item becomes challenging. Historical product data has two main components: sales data and product image data. Image data entail information about attributes of the item, such as colour, style, pattern, and various other essential features. Historical sales data for building forecasting models are not representative of all the product aspects; therefore, they need to be complemented with additional data such as product image data, social media data, and consumer data to predict the fashion apparel demand. Newly arrived fashion product items may differ from the existing products in many ways; however, there could be many of its similar features, such as colour, size, and style, etc. present in the historical product data that could be extracted, and their impact could be explored for forecast modelling.

2. Deep Learning for Demand Forecasting in the Fashion and Apparel Retail Industry

A number of forecasting methods have been developed and employed in the fashion retail industry over the past few years. Statistical approaches, such as regression modelling, are used in [11] for the sales forecast. Linear time series forecasting models such as ARIMA and Exponential smoothing have been widely used for forecasting short-term as well as long-term sales and demands [12][13], Box and Jenkins methods [14] are popular for demand forecasting. However, these methods have limitations in terms of transforming qualitative features of the data into quantitative ones because sales patterns significantly vary in the fashion retail industry [15]. Linear forecast models suffer from significant limitations such as not capturing the nonlinear relationship between various exogenous variables, outliers, missing data, and nonlinear components that are often present in actual time series data [16].

Machine learning and deep learning models such as the support vector machine [1], neural network [17], and recurrent neural network [2] are among many forecast models that have gained popularity among forecast researchers and practitioners given their ability to overcome the drawbacks of traditional linear forecast models. NN models are considered the most efficient forecasting methods, as they have demonstrated high performance in various studies [18]. In [19], the NN model is used to forecast weekly product demand in German supermarkets, and its forecasting performance was found to be high. In another comparative study by [20], the NN model's performance for forecasting aggregate retail sales was reported better than traditional linear statistical forecast models, and it was found to have effectively captured the seasonality and dynamic trends in the time series sales data. The backpropagation NN model is one of the NN model variants that was found to have generated a highly accurate forecast of sales profile in [21]. Moreover, the NN model is found to be effective at de-seasonalising time series data in the study by [18] that traditional linear models fail to do. A hybrid model integrating a genetic algorithm and NN forecast model is presented in [22] to improve the sales forecast's accuracy.

The major shortcoming of traditional linear forecast models, as well as expert algorithms, is that they cannot learn from unstructured data such as text data, social media data, and image data. Product image data analysis can provide valuable insights and can be used for forecasting sales from historical sales data and product image data. Machine learning methods are popular for dealing with various data types, both structured and unstructured data. Image clustering is one of the widely used advanced machine learning techniques that discover similar image features from the image data and categorises them into clusters based on the degree of similarity [23].

Laney and Goes [24] highlight that data mining has gained popularity with the introduction of big data. Data mining and artificial intelligence overcome the problems of the classical approaches to forecasting problems [25][26]. Recently, the growing popularity of deep learning models and their advantages in solving data mining problems over traditional models has attracted more attention from the scientific community from forecasting research [27]. Deep learning has found a plethora of applications in many areas, and significant research has been done on it in the medical [28], transportation [29], electricity [30], and agriculture [31] fields. Sales prediction was performed in various studies, such as [26][31], for different product categories using machine learning methods. In another interesting study by Thomassey [32], clustering and NN are combined to predict long-term fashion sales using historical sales. Significantly, the CNN model has been gaining popularity in image recognition and clustering since 2014 [33].

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