**Introduction**

The timely and accurate assessment of future sales, is acknowledged as sales forecasting or sales prediction, can provide valuable insights to industries tangled in the manufacturing, supply chains, or trade of goods in today's increasingly competitive and continuously varying business environment. Short-term forecasts are mostly useful for production scheduling and stock management, however long-term forecasts can assist in corporate growth decision making [1]. Due to the high competence in food market, the sales forecasting and inventory management plays a key role for the profiting of the business. Sales estimation is also vital in food business due to the short lifecycle of the many goods. the inaccurate sale forecasting led to loss of revenue in case of deficiency and overweigh situation and it will directly or indirectly impact the business in term of profitability [2]–[6]. The influence is not restricted to economics; an inefficient estimating system can also influence the customer service quality. For instance, if a buyer is dealing with a stock-out condition, he may select to shop at a different store [7]. Furthermore, the numerous items in the food industry are known for having long supply chains consisting of multiple stakeholders (such as vendors, manufacturers, distribution partners, and retailers), resulting in orders being sited before an intimate assessment of the consumption rate for the goods [8], [9].

Despite its importance, sales estimation is a difficult issue to master because the achievement of a items sales is strongly reliant on the individual preferences of customers [10], [11]. Furthermore, the lifecycle of food products is often quite short, with new goods with no prior sales statistics being introduced. Food assemblies are also made up of a massive number of distinct items in a variety of flavors and volumes, which correspond to a big number of different stocks keeping units (SKUs). Furthermore, due to factors such as pricing, promotions, fluctuating customer preferences, and weather condition, food consumer demand is continuously fluctuating that directly impact the sales [5], [12], [13]. Also, the retail food supply consists of a wide range of perishable commodities with short shelf lives and varying storability, making forecasting food sales a difficult process. Managers generally forecast sales based on their own preferences. The accurately forecasting of food sale by retailing manager will lead to the growth in sale, customer satisfaction, and reduce the food wastage. Skilled managers, on the other hand, are hard to come by and aren't available at all times (e.g., they may get sick or take a leave). As a result, sales forecasting should be facilitated by automated structures that can act as a trained manager when he will unavailable and/or assist him in making the best possible result by providing projections of future sales. One technique to develop such a system is try to replicate the expertise of talented administrators in a computerized system. Instead, machine learning techniques can be used to automatically develop reliable sales forecast models using the richness of sales figures and related material. The latter is a simpler procedure that is not influenced by the preferences of a single marketing executive and is dynamic, means it can respond to deviations in data. Additionally, it has the ability to outperform a human expert's forecast accuracy, which is often flawed.

Based on the aforementioned factors, accurate sales forecasting is essential for production policy and business improvement. The complexity of underlying sale forecasting system can also be demonstrated by the published studies. In practice, food trade prediction can be done on the basis of quality, quantity, or in a combination of the qualitative and quantitative method. When there isn't enough data to make a quantitative evaluation, qualitative methods are used instead. Either mathematical techniques with causative variables or extrapolation of previous sales records are used as quantity base methodologies. Time series models, causal models, and composite models are the three types of quantitative approaches. Cause–consequence associations between sales and demand affecting factors are used in causal models. To forecast future demand, time series models use previous sales time series information collected at regular time intervals. The time series and causal models are combined to develop the hybrid models.

Forecasting accuracy in the food retail sector is heavily dependent on the forecast horizon. The goods’ shelf life is a noteworthy factor in determining the forecasting time horizon. Especially, the fresh foods like fruits and vegetables that have very short shelf life also require the short term estimation to avoid unnecessary and inadequate stock [14]. In food retail, the demand patterns are based on the customers and foods. The demand of the food can be fluctuated and normally categorized into three different types: short term fluctuations due to holidays and promotions, medium term fluctuations due to summer vocations and weather seasons, and the long-term fluctuation due to economy [15]. The variation in customer demand makes the forecasting of food difficult to accurately predict what will be needed and what will be ordered. The variation in customer demand causes the understocking and overstocking error [16]. Overstocking errors lead to insufficient shelf space, promotion, and product wastage while the understocking error reduces the sales profit, customer confidence and market image. As a result, in order to increase forecast accuracy, these impacting elements must be taken into account in the forecasting model. The ultimate goal of a prediction model is to site an order depending on the outcome of the forecast.

Despite the fact that the estimation models have been much accurate, there is always some uncertainty in the forecast, which influences stock managerial decisions [17]. To solve this problem, quantile predictions should be used rather than the point predictions or extrapolated quantiles. Incorporating these considerations in attention, the goal of this research is to create a time series model with inherited outdoor factors to anticipate regular sales of a fresh item. This research study aims to help with sales forecasting challenges by:

1. This research study aims to help with sales forecasting challenges by:  The models offered to address with this challenge in the existing literature mainly incorporate a slight number of parameters that impact sales;
2. Assessing the ability of deep neural networks (DNN) to predict future events in the context of food retail sales forecasting. Deep learning's application in this area is still in its early stages and deserves more investigation. It also aims to compare the DNN model's performance to that of 4 basic data mining regression techniques in order to determine whether using more complex methods improves accuracy of forecasting model significantly or if simpler procedures may produce similar outcomes.
3. Development of forecasting deep learning model in the context of food retail, in which field experts' opinions and product features are merged and included in the model as predictive variables.

Although the focus of proposed research is on the food retail business, but the suggested models can be use in other retailing areas due to the complications are often comparable: a dataset of historical evidence to guide forecasts, forecasting required for new items in future for that no time series records are offered, a comprehensive archive of the attributes of traditional and contemporary items, and no intersect of products between seasons.

There are multiple sections to this work. A survey of prior studies on the use of data analysis practices for estimation models is included in the next section. Section 3 describes the case study as well as the data that was studied. The Methodology section (Section 4) explains the used methodology used as well as the performance evaluation measures. Section 5 summarizes all of the results and includes a discussion of the findings. Eventually, the work's conclusions are offered, along with suggestions for further work.

**Literature Survey**

Most sales forecasting academics have presented new prediction methods, assessed the capabilities of standing ones, or updated standing ones depending on applications during the last several decades [18]. The methods include everything from a basic moving average to a sophisticated machine learning model. However, when compared to other fields, the number of research publications in the area of food sales estimation is quite low.

**Food sales forecasting**

For a large Victorian food distributor, *Kong and Martin, 1995* [19] used a back propagational neural network (BPNN) to anticipate forthcoming sales growth of a food items. They also concluded from the findings that bad parameter selection in the BPNN model can result in sluggish convergence and/or inaccurate output. Chang (1997) [20] introduced a ambiguous forecasting practice for seasonality in time series food sales data to address the uncertainty in seasonality. In his research, he looked at both seasonal and trend fuzziness. To estimate the sales of fresh and hygienic milk for dairy product manufacturing company, *Doganis et al. (2006)* [21] offered a nonlinear time series estimation model that is the integration of two algorithms (genetic algorithm and radial source function NN). They also demonstrated that when equated to other linear and nonlinear time series prediction models, the adaptive neural network produces lower forecast error. However, the number of nodes in the NN and the parameters for the genetic process make this model complex. In the study of Taylor (2007) [22], he proposed an exponentially weighted quantile regression approach to generate regular interval estimation based on quantile predictions. When time series data are extremely instable and distorted due to risky values, he also suggested using the interval forecasting technique. When compared to standard procedures, his method produces better results. *Chen and Ou (2009)* [23] created a model for forecasting perishable good sales in a store that incorporates grey relation analysis and a multi-layer network. They demonstrated that this model reduces forecast error by a greater percentage than other quantitative time series models like moving average (MA), generalized autoregressive conditional heteroskedasticity, autoregressive integrated moving average and ANN like BPNN, Generalized BPNN. Hasin et al. (2011) [24] proposed using an ANN to estimate sales of certain goods (particularly perishable items/foods) in a Bangladeshi retail setup. They also demonstrated that, in terms of MAP, fuzzy ANN outperforms the Holt-Winters model in forecasting. The study proposed by  [25] used BPNN to create a quick and convenient store sales prediction system and compared the findings to MA and logistic regression. Shukla and Jharkharia (2013) used an ARIMA (autoregressive integrated moving average) pretrained model to estimate vegetable demand on a regular basis in the vegetable wholesale market of India with a MAPE of 30%. In a study presented by *Zliobaite et al.* (2012) [26] investigated the case of food distributor (Sligro Food Group N.V.) and provided a two-level switch model. This method of sales estimation divides time series sales into random and predictable categories, then applied an intelligent forecaster for predictable sales and a MA for random sales.

**Hybrid models**

There is no common modelling approach that can be used to solve a variety of issues. For instance, it is unlikely that a model that accurately estimates the cost of the product will also accurately estimate demand for the same product. As a result, significant prediction accuracy can only be achieved if more than two models with various capabilities are joint and implemented, rather than a solo limited-capability model.

To estimate daily beer sale in the Slovenian market, *Bratina and Faganel (2008)* [27] established an ARMAX (Auto Regressive Moving Average with External Variables) model. In the proposed study of *Cools et al. (2009)* [28] he used together ARIMAX and SARIMAX models to predict the count of traffic on daily basis. For the Indonesian market, Lee and Hamzah (2010) [29] created an ARIMAX model to estimate the Muslim boy’s monthly sale of clothing. This model used linear regression with a combination of ARIMA model and the calendar fluctuation consequence during the Vacation which produced excellent forecasting outcomes than the decomposition technique, SARIMA, and ANN. In the proposed study of Chekov and Sigauke (2012) [30], he used the SARIMA and regression-SARIMA to forecast the peak electricity consumption on daily basis in South Africa. Cornelsen and Normand (2012) [31] proposed a model in which he utilized an ARIMAX model to calculate the effect of smoking prohibition on bars in Ireland's. A study proposed by Trancart et al. (2013) [32] used the fish movement dataset of two fishing site in Brittany with SARIMAX model to minimize eel fatality during movement and optimize turbine shutdowns. Kongcharoen and Kruangpradit (2013) [33] implemented an ARIMAX model with a composite key indicator as an external variable to estimate exports volume from Thailand to its trade associated countries on monthly basis.

Many previous studies produced hybrid (S)ARIMA ANN models next to composite (S)ARIMA linear regressors. Luxhoj et al. (1996) [34] firstly built hybrid econometric ANN approaches, which they used to predict total monthly sales of consumer items for a Danish industry. They combined the different component in their model including an annualized time series model, an econometric model with delayed peripheral factors, and an ANN model. The study proposed by Zhang (2003) [35], suggested a composite ARIMA ANN model that perform well among the separate models for different datasets including Wolf's sunspot dataset, Canadian lynx dataset, and exchange rate time series dataset. Aburto and Weber (2007) [36] introduced a hybrid SARIMA and ANN model to anticipate daily demand in a Chilean retail market. The proposed model by them showed the significant results compare to other model like SARIMAX, unconditional average, seasonal naive, existing naive and numerous NN models. Most of them attempted to implement the composite ARIMA ANN model in many domains of application based on these findings. Maia et al. (2008) [37] used a hybrid ARIMA ANN model to predict interval valued time series of weather and stock price data and compared it to AR (auto regression), ARIMA, and ANN models. To estimate air quality in Chile, Diaz-Robles et al. (2008) [38] developed a composite ARIMA ANN model. To predict the wind speed, Cadenas and Rivera (2010) [39] proposed a study in which he develop a composite ARIMA ANN model. To increase the accuracy of wind speed prediction model, the proposed study of Shukur and Lee (2015) [40] used a hybrid kalman filter (KF) and proposed the KF based ANN (KF-ANN) model. Jeong et al. (2014) [41] suggested a composite SARIMA ANN model that was revealed to be more accurate than the classical SARIMA model in estimating annual energy cost budget (AECB) of educational services in South Korean. Using a generated data set as well as actual datasets such as sunspot dataset, energy pricing dataset, and stock market dataset, Babu and Reddy (2014) [42] proposed a composite ARIMA ANN model that has more accuracy when compared to other solo models and current composite ARIMA ANN models.

In the proposed study of Choi et al. (2011) [43], he developed a hybrid predicting strategy that integrates the SARIMA forecasting model and the wavelet transform (SW) to demonstrated that it outperforms the conventional SARIMA model, evolutionary neural networks (ENN) and the classical seasonal decomposition (CSD) with linear extrapolation seasonal adjustment (LESA) method, in terms of prediction computational efficiency. Nie et al. (2011) [44] proposed a hybrid method for short-term demand estimating for power management that combines ARIMA and support vector machines (SVM). Aye et al. (2015) [45] used dataset of aggregated retail sales on monthly basis in South Africa to examine 26 prediction model (23 individual and 3 composite). They discovered that composite prediction allows them to incorporate and dismiss data from a wider number of forecasting models. The discounted combination forecast model (DISC) showed significant results compare to all other solo models, as well as the other two hybrid forecast models. To avoid the disadvantages of ANNA, RIMA, and ARIMAX, Pektaş et al. (2013) [46] presented an integrated ANN model to estimate monthly runoff parameters. To optimize the prediction performance of individual models, Kriechbaumer et al. (2014) [47] used a composite wavelet ARIMA methodology for predicting prices of aluminum, lead, copper, and zinc on monthly basis.

**Demand influencing factors**

Generally, the Customers' behaviors are reflected in the demand affecting variables. Numerous factors of food sale forecasting have been discovered in literature that directly fluctuate the customer demand related to food products.    In their proposed ARIMA-ANN prediction models, Aburto and Weber (2007) [36]used different forecasting parameters including price, payment, intermediate payment, festivals, before holidays, school vocations, holidays, and climate as input neurons. In the presented study of Ali et al. (2009) [48], he proposed the regression tree prediction technique by using the price, promotion, and discount percentage as forecasting input parameters. Ramanathan and Ramanathan et al. (2010) [49] reviewed at the demand determinants that influence an emerging soft drink company’s sale in the United Kingdom. They used structural equation modelling to explain demand structures for distinct product families by considering different forecasting factors like kind of promotion, promotion duration, promotion size, discount percentage, temperature, events, holidays, weekends, product ranking, and customer reviews about the product. They also looked at some research on identifying demand-influencing elements. For the forecasting of food sales Lee and Hamzah (2010) [29] proposed a study which deal with the calendar effect of vacations. Separately from time series data as input variables, Hasin et al. (2011) [24] acknowledged holidays (both regular and festival vacations), promotion strategy, price, availability, utilization rate, brand loyalty, and weather as demand impacting elements in his Artificial neural network base forecasting technique. In their intelligent model, Zliobaite[26] et al. (2012) also used the external forecasting variables including holidays, events, school holidays, climate (temperature, wind, and rain) and promotions (size, duration). Location attributes, promotional factors, weather, public holidays, and product features were all explored by Poel (2010) [50] and Peters (2012) [51] as demand impacting significant factors. They used multivariate linear regression model to forecast promotional sales using these independent features. In their ANN method, Kumar Sharma et al. (2012) [52]took into account temperature, week days, vacation, and the sale of alternative items.

Furthermore, numerous studies highlighted the impact of weather in forecasting demand. Agnew et al. (1995) [16] investigated the food and beverage sector's weather sensitivity in the UK retailing and transportation sector. The potential and benefits of employing meteorological data in the retail market were extensively examined in their research. They also talked about the various factors that cause the demand. In-store sales, advertisements, merchandising, price adjustments, modifications in retail locations, management restructuring, and operational system restructuring are examples of internal factors. Financial reasons, legal and political issues, technological advancements, societal trends, seasons, vocation period, and weather variations are all examples of external causes. Fearne et al. (2006) [53] stressed the need of taking weather into account while selling soft fruits. Mirasgedis et al. (2014) [54] established a demand model that takes into account primary climatic factors (temperature, rainfall, sunshine hours, and humidity levels), secondary weather variables (apparent temperature), economic indicators (visitor behavior), and moment (month of the year and season of the year).

On the basis of research objectives and reviews from shop managers the demand impacting aspects can be categorized in to Festivals, climate, season, cost, replacement and cannibalization, product features, and the frequency of client visits. The cost and the features of the food product are internal factors that can be controlled. However, replacement and cannibalism are partially internal processes that cannot be completely controlled. However, the other factors are uncontrollable external influences. Except for cultural events, and school holidays, the events are divided into regular holidays. Wind temperature, rainfall, snowfall, sunshine period, windspeed, and humidity levels are all factors that affect the climate. week day (weekly seasonality), month day (monthly seasonality), month of the year (yearly seasonality), yearly seasons, and yearly quarters are the many types of seasonality. The pricing is divided into two categories: regular and discounted. Promotion and discount are two types of price reductions. The price drop of the chosen items may have a cannibalization impact on similar item in the same shop and/or in competitors' outlets. Promotion, discount, or stock-out for comparable kinds of items in the same shop and/or in competing stores are all examples of substitution and cannibalism. Promotions for comparable items (in the same shop and/or in retail stores) frequently result in cannibalization of the specific product. On the specific item, discounts for related types of items (in the own shop and/or in competing outlets) have both substitution and cannibalization impacts. Similarly, when identical kinds of items are out of stock (in the same shop and/or in competing stores), the chosen product serves as a substitute. Product freshness, package volume, quality of product and appearance, and shelf life are the different categories of product attributes. The judgments of shop management (when discounting or disposing) and consumers determine the product freshness and appearance. The physical state of a product, such as damage, smell, and mild, is referred to as product quality. The shelf-life of a product refers to how long it will last in the store once it is purchased. The number of customer visits is divided into three categories: regular buyer, inconsistent buyer, and exceptional users (e.g., tourists).

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