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**Forecasting sales for aesthetic products using Machine Learning**

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A dissertation submitted to the Institute of Information and Communication Technology in partial fulfillment of the requirements for the degree of Bachelor of Science (Hons) in Business Analytics

# Authorship Statement

This dissertation is based on the results of research carried out by myself, is my own composition, and has not been previously presented for any other certified or uncertified qualification.

The research was carried out under the supervision of Alan Gatt – Forecasting sales for aesthetic products using Machine Learning, Rushayeal Galea Massa

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# Acknowledgements

# Abstract

In this study, aesthetics sales data obtained from a company based in the UK is used to train and test the data using different machine learning algorithms, and to forecast the results. In this data, the Covid-19 sales period is included, and questions related to the effect caused by the pandemic are answered in the research conducted. This research was carried out to have a detailed analysis of the sales made between the year 2015 and the year 2022 and highlight any patterns and trends which may occur in the data. The problem faced during this research was related to the categorical values which are present in the original dataset so to eliminate this issue, one-hot encoding was used to transform the data. To carry out the forecasting, Random Forest, XGBoost and Neural Networks were used. The algorithm that performed the best of all the experiments tried out was Neural Network with RMSE results as low as 0.98. The data was tested out on different time periods to analyse the patterns and trends further. The time period used were summer, winter, the whole 2019 year, Covid-19 period and the last 3 months of the data. During each time period, each algorithm was tested out for each category one by one. This was done since the sales of the categories vary from one another and the result cannot be predicted correctly if all the sales of the categories are combined. From this study it was found that the Covid-19 pandemic did have a negative effect on the sales of this company as they decreased substantially from the sales of the previous year. It was also found that machine learning algorithms are an efficient solution to be used when predicting supply and demand for aesthetic products. From this research, it was found that the Covid-19 pandemic did not have the same impact on all the regions in the UK as (to be reviewed later with visual). Based on the analysis of the recent data gathered during the year 2022, the sales started returning to the back to the high level of sales which occurred before the pandemic affected the UK and Ireland.

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# Chapter 1: Introduction

## 1.1 Research Problem

This research is based on the sales data of a UK based aesthetic company. The gathered data includes the sales transactions which occurred from 2015 to 2022. The transactions are available for 26 different products which are sold by the company. The quantity feature will be used later to look for any patterns or trends which might be present in the dataset. In addition to trends and patterns, seasonality and any other possible events will also be investigated.

For this type of study, there are various machine learning algorithms which can be evaluated, since algorithms can perform differently on the same dataset. These machine learning algorithms will be used to predict sales data so that if the result is accurately forecasted, these algorithms can be used to predict future data. The Covid-19 sales periods will be analysed in this research to be able to determine if the pandemic had any effect on the sales of this company. This will be conducted so that the company can reduce their costs and meet customer demands in a most efficient manner. Other time period will also be analysed such as summer, winter, one whole year and the last three months of the data.

## 1.2 Research Question

In this study, the research questions are:

- Did the Covid-19 lockdown affect the sales of aesthetics products?

- Did the Covid-19 pandemic have the same impact on all the regions in the UK?

- Can machine learning algorithms be used to make a prediction for supply based on previous transactions?

The main hypothesis stated for this study is that Covid-19 did in fact affect the sales of aesthetic products. This hypothesis was formulated due to the negative effects other non-essential businesses experiences during the Covid-19 periods. The hypothesis for the second research question is that the effect was approximately the same for all the regions in the UK since the lockdown was enforced on all the UK regions. The hypothesis formulated for the third research question is that machine learning can be used to make predictions for a supply based on previous transactions, given that enough useful information in the correct format is provided.

## 1.3 Aims and Objectives

Sales forecasting is used in many businesses nowadays as this is very helpful when it comes to making orders and planning production for certain products. This is especially helpful when it comes to planning supply and demand for products which have a short expiration date. The aim of this research is to find out how the Covid-19 pandemic affected the company’s sales and in what way were they affected. Another aim of this research is to find out the Covid-19’s effect on the regions in the UK. The company will also have a forecasting solution which is already tried and tested against their data to help them finalise any future orders. They will also be provided with a detailed analysis of the product quantities which were sold during different months for different categories. The risk of over-ordering too many products or not meeting the customer demands will be reduced as they can easily generate an estimate of the supply and demand. The company will know more regarding which seasons are more successful and which are the most sold products from their ranges, together with the most popular categories. This study will also be very helpful to the company when it comes to planning and providing training seminar related to their products since they can choose on what to focus them more about. Since the findings will also be compared between different regions across the UK, this will determine how regions were impacted.

## 1.4 Purpose Statement

The reason why this research was chosen was that data analysis is a very interesting subject to explore in a more realistic scenario. The data was gathered through a personal contact who is working in a company that distributes aesthetic products mainly across the United Kingdom and a few other countries such as USA and Brazil. Data analysis techniques will be used to identify the patterns which are present in this data. Machine learning forecasting techniques will also be used to help them formulate a better marketing and supply strategy depending on the current and future market demand and find out which is the optimal algorithm to be used on this dataset. The reason for choosing to conduct this research using this approach is that it saves more time when trying out experiment using computerised methods rather than statistical model. This is especially suitable since the dataset is also larger in size.

# Chapter 2: Literature Review

Forecasting is the process of making predictions based on past and present data. Forecasting is used by industries and business entities, including aesthetic companies to research the supply and demand for their products. This assists industries in controlling the market chains.

## 2.1 Sales Forecasting:

Forecasting entails making predictions about the expected future demand and supplies. This is useful so that the customer demands, and the supply requirements are met.

### 2.1.1 Meeting customer demand

In businesses, past sales information can be used to forecast the future sales for the immediate months. Forecasting in companies is used, so that the business can have a general grasp of the market demand and help to set goals and plan resources and logistics for this demand. Due to the increase in the use of AI technology, competition in the market is growing at a more rapid pace [1]. The company can also have an indication of what type of services or products are more popular with clients and in what ways are the trends and patterns are changing and evolving. If the company does not satisfy the market demand for a product, customers will have to opt to purchase from competitors, which will then result in loss of sales and possibly even losing the customers’ loyalty. A business can get all the demand information by applying their sales data to any of the desired forecasting models and increasing the chances of improving the satisfaction levels of its customers.

### 2.1.2 Cosmeceutical products supply and demand

Cosmeceuticals are the products which fit the niche between drugs and cosmetics. This term is used in the professional skin care industry to describe a product that has measurable biological effect in the skin but is regulated as a cosmetic since it claims to affect appearance. These professional skin care products come in the form of sunscreen, antiaging creams, foundation, facemasks, derma fillers and more. Cosmeceuticals are the fastest growing segment of the personal care industry and their formulations have expanded from skin to body to hair and several cosmeceutical treatments for conditions. Studies focusing on the cosmeceutical products highlight that there will be strong growth perspective for this industry in the coming years [2].

#### 2.1.2.1 Seasonality

Seasonality stands for regular patterns that are determined by different seasons over a given number of periods. Seasonality in terms of sales refers to the oscillations in total amount of sales that occur throughout one year and then repeats in the following years. Seasonality is not determined by the volume of sales of the whole year but in volumes during specific periods. This periodic seasonality can be based on short volumes such as weeks or months [3]. In an industry, seasonality in sales is highly influenced by the different seasons of the year, holiday periods such as summer breaks or Christmas holidays, and other notable dates such as Mother’s Day, Father’s Day, or Valentine’s Day. When a forecast is predicted based on seasonality, the accuracy must be very high because if the forecast is inaccurate, this may cause major issues in marketing, production, investment, and expenses. If the marketing and advertisement is not scheduled in the correct seasonality, the targets will not be achieved and the money for campaigns would not have the desired effect. Over production of products cause by incorrect seasonality can also be an issue as certain products have to be sold in a specific period of time. If these products are not sold in this period of time, they may have to be either thrown away or sold at a very cheap price that does not cover expenses.

#### 2.1.2.2 Shelf life

Once a product is produced, this product is labelled with an estimated shelf life. This shelf-life duration depends on the product itself which can be either a small number of days or it may still be good for several years. Products which are natural with less chemicals or additives tend to have a shorter shelf life than products with preservatives and additives. Shelf life is a very important feature in a product as it determines if the product is still safe to consume or use and guarantees the quality of the product. When a customer purchases a product which usually has a shelf life of more than one year, they would not expect the product to expire in a couple of days or months.

### 2.1.3 Extraordinary events affecting supply and demand

When an extraordinary event happens around the world, this may influence the sales of businesses which can lead to either a decrease or an increase of sales of certain products.

#### 2.1.3.1 Covid-19

The global pandemic in 2020 lead to a worldwide lockdown which affected the worldwide economy and stability [4]. To slow the spread of COVID-19, governments enforced social distancing restrictions and lockdowns on businesses deemed nonessential. The essential businesses were also enforced by restrictions, yet they were less drastic. According to research done by Fairlie and Fossen [5], from February 2020 to April 2020, the number of active business owners dropped by 22%. Year-over-year sales usually increase by 3% to 4%. However, in the second quarter of 2020, sales decreased by 17% whereas online sales increased by 180%. It was found that sales losses were largest in businesses affected by mandatory lockdowns such as accommodations, drinking places, and arts, entertainment, and recreation [5].

In the UK, a 19.8% decline in Gross Domestic Product (GDP) was caused by public health measures such as social distancing, travel restrictions, and the closure of non-essential businesses between April and June 2020.The biggest quarterly recession in household expenditure ever occurred over this period, when spending on dining out, lodging, transport, and recreation decreased by over 20%.

The 11.6 million jobs affected by the furlough plan considerably lessened the labour market's effects, causing the unemployment rate to increase from 3.8% at the end of 2019 to 5.2% at the end of 2020.

Following the removal of restrictions, the GDP increased by 17.6% in the third quarter of 2020, from July to September. In the third quarter of 2020, household expenditure increased by 19.6%, including increases in dining, lodging, and transportation costs. Average home prices increased by 13.5% in the year leading up to June 2021.

Despite the Delta variant's emergence and the following lockdown causing a 1.2% GDP decline over the first three months of 2021, the remainder of the year saw incremental growth. In spring and summer of 2021, household spending increased once more, returning steadily to pre-coronavirus pandemic levels by 8.5% and 2.6%, respectively.

By the first quarter of 2022, GDP had restored to pre-coronavirus pandemic levels[[1]](#footnote-1) [6].

#### 2.1.3.2 Brexit

As the UK officially exited the single market and customs union at the end of the transition period on December 31, 2020, which was the result of the June 2016 referendum, trade with the EU initially dropped.

According to research found, the Brexit process is estimated to have reduced the level of UK productivity by between 2% to 5% over the three years since the referendum [7].

It is challenging to separate the economic effects of Brexit from the COVID-19 pandemic, the disruption of the global supply chain, and the increases in energy and food prices since they all overlapped [6].

#### 2.1.3.3 Change in Government

Since 2015, the UK has had five different prime ministers in the government. David Cameron was the prime minister between 2015 and 2016. Between 2016 and 2019, Theresa May was elected prime minister. Boris Johnson acted as a prime minister between 2019 and 2022 followed by Liz Truss in the same year. Rishi Sunak is the current prime minister of the UK since 2022.

## 2.2 Machine learning:

Machine learning is a field devoted to understanding and developing ways that allow machines to learn approaches that use data to enhance computer performance on a set of tasks.

### 2.2.1 Introduction to machine learning

Machine learning is a set of algorithms found in the Artificial Intelligence (AI) discipline, which allows a computer to predict outcomes without being specifically programmed to do so [8]. This type of AI is becoming more popular and widely used in fields such as banking and finance, real estate, healthcare, retail, education, insurance, and pharmaceuticals [9]. The main objective of machine learning is to identify patterns based on predictors and then be able to use these patterns to predict an outcome on unseen data. These models can be trained more than once, given related-context data to be able to predict future data and make necessary decisions [10].

If an algorithm is well trained, it will be able to learn very complex scenarios and predict the expected data with high precision. The choice of the correct predictors is very important when training a machine learning model [11]. Besides forecasting data, due to its versatile nature, machine learning can also be used for facial recognition, car identification, detecting credit fraud, detecting spam, providing personalised recommendations and services, and virtual customer support amongst others [12]. Machine learning is made up of different algorithms, each using different mathematical models to fit data and be able to conduct predictions. Some commonly used algorithms are Linear Regression, Decision Trees, Random Forest, KNN and K-means.

### 2.2.2 Machine learning approaches

There are different approaches for machine learning; most common are supervised learning, unsupervised learning, and reinforcement learning. Each of these techniques works by implementing different algorithms which process and learn data in different ways.

The main difference between supervised and unsupervised techniques is that supervised training requires the programmer to label data beforehand in order for the machine learning algorithm to predict an outcome (focuses more on classifying the data using labels), while unsupervised focuses more on clustering the data, reducing dimensions and identifying sequences by association [13].

Supervised Learning is commonly used in sentiment analysis, predictive analysis based on regression or categorical classification, natural language processing, detecting email spam and image classification. Some algorithms used in this approach are Decision Tree, Random Forest, Support Vector Machines and Linear Regression. Unsupervised learning is mostly used in scenarios of speech processing, object categorisation, audio classification, and automatic labelling. Commonly used algorithms for this approach are K-Means, Hierarchical Clustering, Density-Based Clustering and A-priori. Algorithms which can be implemented in both supervised and unsupervised learning are Naïve Bayes, Auto Regressive Integrated Moving Average (ARIMA) and Deep Learning.

Reinforced learning includes techniques like deep Q-network, post-decision state, Dyna-Q and Q-learning. These methods assist IoT devices in selecting security protocols and key parameters for various threats through trial and error. As an example, Q-learning is used as a model-free technique to enhance malware detection, offloaded anti-jamming, and authentication performance.

## 2.3 Forecasting supply and demand:

Nowadays, forecasting using computerised methods has become a very popular process that is used in different fields to be able to make predictions of future data based on past data. As stated by Petropoulos *at al.* [14], in around 15 years, the field of forecasting has seen amazing growth in both theory and practice. Using today’s advanced technology, one can immediately get a detailed hour-by-hour weather forecast. In this forecast, the temperature, rain, weather conditions, UV index, wind and much more are predicted. Probability forecasts are used when uncertainty is irreducible, for example it can be used during elections to forecast which party will win the election. This does not necessarily mean that the party forecasted to win will surely win, but there is a great possibility that the forecast is correct. Forecasts can also be utilised in companies when they are selling a service or products to predict future sales based on the past sales made [14].

All these forecasts can be estimated based on using multiple past parameters called the predictors. This prediction is made available using the different algorithms found in machine learning to be able to not only forecast upcoming data, but also help in decision-making and analysing current status such as the company’s performance. The information based on the forecasting can help businesses to allocate resources, anticipate expenses and plan their budgets wisely. When it comes to predicting sales, one can also have an idea of how the production schedules need to be set [15]. When performing the forecasting, one must pay attention to the data being used and how it is used in the forecasting, as if the data is not used correctly, the forecast will not output the correct results either. If a company makes their decisions based on the incorrect predictions, the company may suffer many losses in both target audiences and the sales of products or services.

### 2.3.1 Time Series Modelling

At present, the most commonly used forecasting method of sales forecasting is time series modelling. From the sales data, multiple patterns and trends can be analysed such as trend in sales, seasonality, autocorrelation, patterns caused by the impact of external factors, pricing, and competitors’ behaviours [16]. Sales prediction can be a very complex problem, especially if the data includes outliers, and missing data. At present, several time series models have been developed to be able to overcome this issue by using models such as ARIMA, SARIMAX, SARIMA, Random Forest, and SVM. To be able to implement such models, the sales data needs to include historical data for a long period of time to capture the seasonality and patterns, while also outliers must also be removed from the dataset before using one of the time series models.

In the Time Series Modelling, different patterns may be present in the dataset. The data can include trends which occur when the data is either increasing or decreasing persistently for a long period of time which does not have to be linear [17]. Another type of time series pattern is the cyclic pattern. This pattern includes repeated fluctuations which are non-periodic, while the duration of these fluctuations is usually of a minimum of two years. These fluctuations are usually due to the economic conditions. A third pattern is the seasonal pattern which reflects the seasonality that is present in the Time Series data. Seasonality is always of a fixed and known frequency [18]. An example of seasonality is like demand for sunblock which will be highest during the summer season.

Since most machine learning models can understand only numerical values, when data contains categorical values, a different approach must be taken. This issue can be resolved by using multiple encoding techniques such as label encoding or one-hot encoding. In the label encoding technique, each categorical variable is assigned an integer [19]. When a categorical feature has more than two values, the label encoding technique may cause some undesired issues as the integers assigned may be misinterpreted by the algorithms as having some sort of hierarchical order. This issue may be resolved by using the one-hot encoding technique. In this technique, several additional features are created based on the number of unique values in the categorical feature. This mapping can have Q number of possible values, into a vector with Q number of elements, where only the element corresponding to the current feature value is “1”, while the remaining elements are “0’s” [20]. This encoding is applied to all the unique variables in the categorical variables.

### 2.3.2 Forecasting Models

When predicting data, several models or algorithms can be used. The most used models for time series are Naïve model, Exponential smoothing model, ARIMA or SARIMA, Linear regression method, Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Decision Trees, XGBoost and AdaBoost. Each model has its own unique algorithm, and the accuracy may vary depending on the data being predicted.

In the study ‘Demand Forecasting Using Coupling Of Machine Learning And Time Series Models For The Automotive After Market Sector’, demand for automotive products is forecasted through different models using historical demand history data along with external factors that influence demand. Machine learning models and Time-Series models are split into two sections and subcategorised to compare the best model [21]. According to the researcher, it was found that the top 3 models of machine learning are ADA-boost, XGB boost and GBM. On the other hand, the top 3 models for time series models are Auto-ARIMA, Naïve, and Naïve-rept. The best model is then selected by calculating the Root Mean Squared Error (RMSE) of each model and choosing the approach with the smallest RMSE.

### 2.3.3 Related Studies

In a study conducted by Akanksha *at al.* [22],store sales were predicted using Linear Regression, Random Forest and XGBoost models. The Linear Regression model’s performance was so poor, that it was not included in the paper. The dataset used contained approximately 2.94 million observations and had 6 variables. In this scenario, the XGBoost gained the best results, obtaining an RMSE of 3.86, while Random Forest obtained an RMSE of 5.13.

As proposed by Huang *at al.* [23], to forecast cosmetics sales, the most appropriate method is LS-SVM. In this paper, the three models which were used are BPNN, LS-SVM and AR model. In terms of Mean absolute percentage error (MAPE), LS-SVM test resulted in 9.21%, BPNN test resulted in 12.56% while the AR model resulted in 17.13%. When evaluating the models using the Pearson Correlation Coefficient, LS-SVM had the highest correlation of 0.91, BPNN had a correlation of 0.86 while the AR model had the least correlation of 0.81.

In a study conducted by Sajawal *at al.* [24], it was stated that sales forecasting is the most challenging task for the inventory management, marketing, customer service and Business financial planning for the retail industry. Therefore, they used different machine learning techniques to perform predictive analysis of retail sales data. The regression models used were Linear regression, Random Forest Regression and Gradient Boosting Regression, while the time series models used were ARIMA and LSTM. The results show that Gradient Boosting Regression performed best with an RMSE of 0.63 followed by Random Forest with an RMSE of 0.69. The model that performed the worst in this study was the ARIMA model.

Vithitsoontorn and Chongstitvatana [25] researched both statistical and deep learning methods when conducting demand forecasting. They concluded that both are reliable and are suitable to be used when predicting demand. The study showed that ARIMAs predictions of the future were made in an average straight line, whereas LSTM predicted the future value based on the seasonality and trend of the data. When the model was trained on the monthly observations of the data, the model provided better error scores. The ARIMA model obtained an RMSE of 21501.66 while the Multivariate LSTM obtained an RMSE of 20693.86.

In a study done by Wang *at al.* [26], they attempted to find a forecasting method to balance their purchasing and sales in retail companies. This study explores ARIMA, SVM, RNN and LSTM in five dimensions which are predictive performance, generalization ability, runtime, cost, and convenience. When it comes to accuracy, SVM and LSTM were the best two models to use both when working with normalised or non-normalized data. It was also concluded that LSTM is the most convenient model to use.

# Chapter 3: Research Methodology

In the research methodology, the process and the steps taken to achieve the goals is explained in further detail. The first step in the process was gathering the data and loading it into Python. Next, data cleaning was performed on the data and a new file was created with the cleaned data. PowerBI was used to explore the data using some visuals and to make initial predictions. The data was then prepared for Machine Learning algorithms such as data training and testing, and the first experiments were tried out. Some evaluations were outputted by the experiments and the results were documented.



**Figure 1:** Pipeline

## 3.1 Data Acquisition

The data used in this study was acquired from an aesthetic company based in London which distributes products mainly to the UK and Ireland.

## 3.2 Data description

The data acquired is made up of 86,765 unique records which each refer to a unique sale. Each sale is made up of 13 different variables, these are shown in Table 1: Variable Description together with a short description of each variable. The data includes all the sales made between November 2015 and March 2022.

|  |  |
| --- | --- |
| **Variable** | **Description** |
| Data Entry Date | When the data was inputted in the system. |
| Pharmacy | 11 unique pharmacy names. |
| Year | The year in which the sale was made. |
| Month | The month and the year in which the sale was made. |
| Quarter | The quarter and the year in which the sale was made. |
| Product | 26 unique product names, each fall under one of the six categories. |
| Qty | Quantity sold for each product. |
| Cust.Name | 4,317 unique customer names which identifies who purchased the products. |
| Comp.Name | 4,299 unique company names which identifies which company purchased the products. |
| Area Code | Full Area code that reflects the regional code in which the sale was made. This is made up of letters and numbers. |
| Sales Rep | Identifies the sales representative who handled the sale. |
| Code | The code of the area but inly the letters are listed. Blank is used for countries outside of the UK and Ireland. |
| Location | 10 unique locations in which the sales were made identified by a number. These represented regions mainly in the UK and Ireland, and other countries such as the USA. |

**Table 1:** Variable Description

## 3.3 Data Cleaning

To be able to make a time-series forecasting of sales, the data needs to be in a numerical form. To do this, some data cleaning is required so that the data will be tailored according to what is needed and clearly understood by the algorithm.

The first step in the data cleaning process was loading the data from the csv file into a data frame and making sure that the data was being loaded correctly. The data was checked for any null values and the totals for each column were displayed. Null values were found to be present in the ‘Cust.Name’, ‘Comp.Name’ and ‘Code’ columns. The null values were ignored and kept in the data as the mentioned columns were not going to be used when doing the forecasting. The columns which were not considered that important when predicting future sales were the ‘Data Entry Date’, ‘Cust.Name’, ‘Comp.Name’, ’Sales Rep’, ’Area Code’ and ‘Code. These columns were removed so that the forecasting process would be made only on the relevant data. The reason why these were irrelevant where because the sales were not affected by names or when the sale was inputted in the system. Regarding the ‘Area Code’ and ‘Code’ column, the location is enough to apply a forecasting algorithm on this data as only the name of the location will be taken into consideration when doing the analysis.

The next step in the data cleaning process was to make changes to the ‘Month’ column. This column was converted from text values to numeric values to make the data in a numerical form as much as possible. The same process was repeated on the ‘Quarter’ column since the data previously included the letter ‘Q’ in addition to the quarter number. As a result, these two columns were completely changed to numerical forms and could now be used in the forecasting process.

The ’Location’ column contained only a number which represented a specific location. This needed to be changed so that the data could be more easily interpreted by seeing the real location listed in the records. This was done by automatically replacing each number with the specific location value for each record found in the data frame.

The ’Product’ column contained some data inputting errors. Some products were typed down differently in certain records such as written all in capital letters instead of capitalising the first letter of each word. This resulted in having to first extract all the unique values found in the column, and then determining which products were doubled. To make the data more practical, each original product name was changed to an identifiable name such as the type of product and a number added at the end. For the products which were duplicated, instead of giving one value to replace, the variations of the products were listed.

A category column was missing from the data. The different products were first analysed, and then each product was assigned to one category. Six different categories were created, and these were added to the original data frame. The new column named ‘Category’ was used to store these values. The next step was assigning each product to a category, and this was done by using dictionaries found in Python.

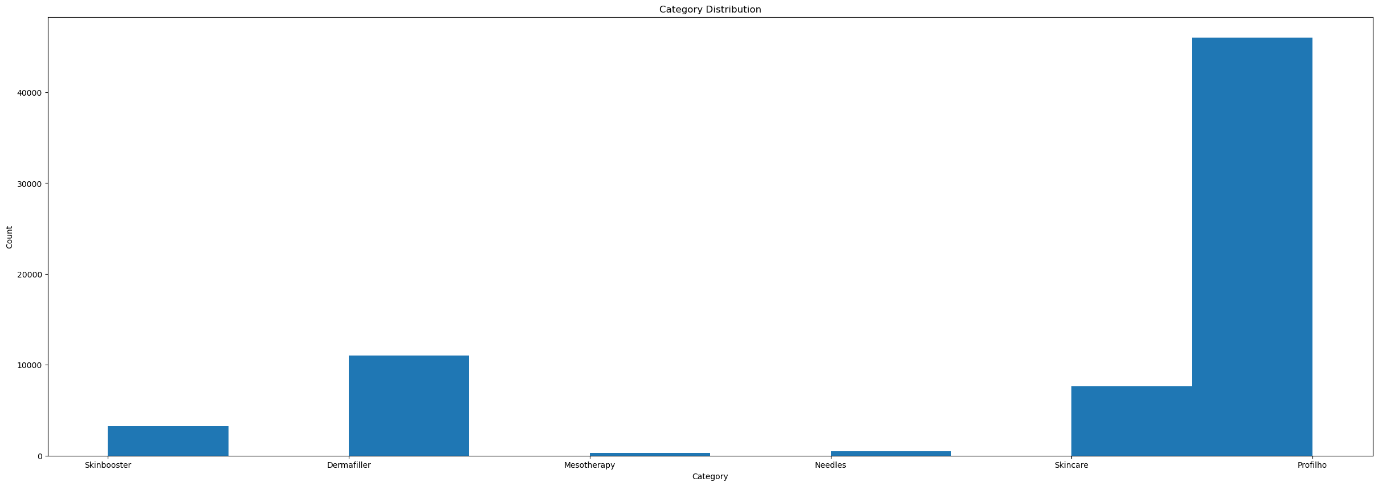
Since the data contained thousands of unique customer names, a dictionary could not be used straightaway to generate the practical names. Therefore, the unique names had to be stored in a variable and then an array was created. A function was also created so that each name stored in the array would be changed to the word ‘company’ and a unique number added at the end. A dictionary was then used to replace the customer’s names with the names found in the dictionary created. A copy of the dictionary containing old and new names was then saved in a csv file so that there would be a reference to the real names. The same process was repeated for the company names and the pharmacies.

The final step in the data cleaning process included removing records containing negative quantities which represented the samples which were given to customers. The new data frame was then saved into a new csv file to be used later in the forecasting methods.

## 3.4 Data Exploration

The data was explored by plotting it against various plot such as Histograms, Boxplots, Pie Charts, and others. The purpose of using a boxplot is to determine if the data contains outliers and if so, in what columns are the outliers present. The purpose of using a histogram is to be able to have a visual representation of how the data is distributed across the different values found in a variable while pie chart obtains the same result but displays them in a pie chart together with percentages.

The distribution of variables can be easily identified when the data is plotted using Histograms. From the histogram shown in Figure 2: Category Distribution, it can be noted that ‘Profilho’ was the most popular category followed by the ‘Dermafiller’ category. In Figure 3: Product Distribution, it is evident that ‘Injection 7’ was the most sold product across all times with the highest quantities.



**Figure 2:** Category Distribution

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Description automatically generated

**Figure 3:** Product Distribution

Using boxplots, it was concluded that from all the categories, ‘Profilho’ contained the highest number of anomalies, while from the products ‘Injection 7’ contained the highest number as well. These two variables were filtered out and a boxplot was plotted for each scenario. These are show in in Figure 4: Category Boxplot and Figure 5: Product Boxplot respectively.

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**Figure 4:** Category Boxplot

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Description automatically generated

**Figure 5:** Product Boxplot

‘Injection 7’ made up 85% of the products sold as shown in the pie chart in Table 2: Product Percentage Table. As shown in Table 3: Category Percentage Table ‘Profilho’ made up 85% of the categories sold while ‘Dermafiller’ made up 8%. As seen in Table 4: Location Percentage Table 20% of the sales were made in ‘London’ followed by 16% made in ‘NorthEast, Midlands’.

|  |  |
| --- | --- |
| **Product** | **Percentage** |
| Injection 7 | 66.44% |
| Injection 10 | 4.41% |
| Injection 3 | 3.89% |
| Cream 2 | 3.88% |
| Facemask | 3.77% |
| Injection 1 | 3.68% |
| Injection 5 | 3.35% |
| Injection 2 | 2.74% |
| Foundation 2 | 1.53% |
| Injection 6 | 1.26% |
| Injection 4 | 1.09% |
| Foundation 1 | 0.64% |
| Injection 8 | 0.56% |
| Make-up Remover | 0.43% |
| Skin Booster Needles | 0.38% |
| Cream 3 | 0.35% |
| Injection 13 | 0.33% |
| Mesotherapy Needles | 0.29% |
| Pills | 0.27% |
| Injection 14 | 0.16% |
| Injection 9 | 0.11% |
| Sunblock | 0.10% |
| Injection 11 | 0.08% |
| Cream 4 | 0.07% |
| Injection 12 | 0.05% |
| Cream 1 | 0.05% |

***Table 2:*** *Product Percentage Table*

|  |  |
| --- | --- |
| **Category** | **Percentage** |
| Profilho | 67.01% |
| Dermafiller | 16.03% |
| Skincare | 11.13% |
| Skinbooster | 4.76% |
| Needles | 0.68% |
| Mesotherapy | 0.39% |

***Table 3:*** *Category Percentage Table*

|  |  |
| --- | --- |
| **Location** | **Percentage** |
| NorthEast, Midlands | 19.57% |
| NorthWest | 15.40% |
| London | 14.28% |
| SouthEast | 10.92% |
| Scotland, Newcastle | 10.42% |
| Outside London the rest | 9.83% |
| SouthWest | 9.56% |
| Outside London M25 | 4.78% |
| Ireland & Norhtern Ireland | 4.68% |
| Brazil, USA, Blank, IE, Zimbabwe, Zurich | 0.56% |

***Table 4:*** *Location Percentage Table*

The trend of the sales data was plotted against a time graph as seen in Figure 6: Time Graph. While this shows that the sales were increasing and growing by time, it also shows very sharp drop in sales during specific times in 2020 and 2021 which hints that sales were affected by extraordinary events.

A picture containing text, plot, screenshot, line

Description automatically generated

**Figure 6:** Time Graph

In the time graph plotted in Figure 7: Time Graph with legend, we can see that Profilho had very high sales over the years followed by the Dermafiller category. By the end of 2020 the Profilho sales spiked up and went back down during the rest of the data.

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Description automatically generated

**Figure 7:** Time Graph with legend

Seasonality was also plotted against a time graph while also highlighting the different months and years of the sales. From the visual shown in Figure 8: Seasonality Graph, we can conclude that November seemed to have the highest number of sales as opposed to the month of April.

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**Figure 8:** Seasonality Graph

In Figure 9: Different Graphs, the trend and seasonality are plotted against a year axis. These visuals help to analyse further if the extraordinary events did in fact have an effect on this sales data.

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Description automatically generated

**Figure 9:** Different Graphs

## 3.5 Data Preparation for machine learning

To choose the forecasting algorithms, the literature review was reviewed, and three algorithms were chosen. The RMSE results from the literature review studies were also noted to be compared later to the results obtained from this study. To be able to forecast the results, the text data used in the forecasting needed to be changed to numerical values. For this reason, as suggested by the previous studies [19] and [20], one-hot-encoding was used on the categorical values in the columns ‘Category’, ‘Pharmacy’, ‘Product’, and ‘Location’. After the one-hot-encoding was performed, the data obtained needed to be grouped by dates. Since the data only includes the month of the sales, all the dates had to be grouped to the first day of the month so that each date is unique and could be used as an index when forecasting. The next step taken in this methodology was to create the lagged features in which the values at prior timesteps that were considered useful were stored. The lagged features go back up to seven time-steps, this means that for each category, the model includes the sales quantity values from the previous seven time-steps as features. The ultimate step taken before the splitting and training of models was to drop any null values which might be present in the data frame.

## 3.6 Training of Models

To train these models, five different types of data splitting were used. The first experiment was conducted on a summer period from the data. The dates which were selected were between the months of June and September for the year 2019. This type of experiment predicted the four selected months of the data and was made up of seven different experiments for each algorithm. First all the categories were used during the forecasting process, and afterward they were predicted one by one.

A second type of splitting was conducted on a winter period from the data. The testing dates were selected between October 2019 and December 2019. This type of experiment predicted the three selected months of the data and was also made up of seven different experiments for each algorithm like the summer experiment. The reason for choosing the summer and winter periods from this specific year is because 2019 was the last year before the Covid-19 pandemic infected the UK.

To have an overview of sales made during each month of the year 2019, the third type of splitting was conducted using one whole year as testing data and the dates chosen were between January 2019 and December 2019. This type of experiment predicted 11 months of the data one by one based on the past data from the previous years. The reason for having one less month in the results, was that January had to be removed from the testing data as it contained null values.

A different data splitting type that was used, was conducted on one whole year during the Covid-19 period which also predicted 11 months of data due to the same reason mentioned before. The testing dates selected were between April 2020 and April 2021, during which two enforced lockdowns happened.

The last data splitting was conducted by choosing the last four months present in the data which were between December 2021 and March 2022. January 2021 was also not included in the forecasting due to the null values. This was conducted to analyse whether the sales had returned to the pre-pandemic level of sales or not.

As suggested by the previously mentioned related studies [22] and [24], to test the forecasting of sales, in this study Random Forest and XGBoost algorithms were used. An additional supervised algorithm which was also used was Neural Networks.

## 3.7 Testing and Evaluation

To test these experiments, all the variations of the models were executed on cleaned test data. A total of 104 unique experiments were tried one at a time. The first test that was tried on each algorithm contained the sales of all of the six categories. The tests that followed, included trying each forecasting algorithm on each category one by one to be able to obtain results that make more sense since not all the categories make the same number of sales.

At the end of each experiment, the RMSE, MSE, R^2, Explained Variance and Max Error were calculated together with an ‘Actual vs Predicted Sales Data’ matrix to evaluate how the tests performed. From the results obtained from each experiment, an evaluation and conclusion were formulated.

# Chapter 4: Analysis of Results and Discussion

This chapter reflects on the results obtained from the experiments that were tried out. The best parameters for each algorithm during each testing period can be found in the Appendix section. In the Appendix, all the results obtained for each category including the differences between the actual and predicted values can also be found.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Summer** | **Winter** | **Whole Year** | **Covid** | **Last 3 Months** |
| **Dermafiller** | 27.96  Random Forest | 24.26  XGBoost | 97.84  XGBoost | 183.05  XGBoost | 67.94  Neural Network |
| **Mesotherapy** | 1.67  Random Forest | 4.58  XGBoost | 3.93  XGBoost | 1.85  Neural Network | 0.98  Neural Network |
| **Needles** | 1.98  XGBoost | 17.72  Neural Network | 15.65  XGBoost | 22.03  XGBoost | 1.90  Neural Network |
| **Profhilo** | 318.10  Neural Network | 1320.98  XGBoost | 1103.03  Neural Network | 818.93  Neural Network | 814.83  Neural Network |
| **Skinbooster** | 33.95  Random Forest | 51.87  Neural Network | 61.91  Neural Network | 21.42  Random Forest | 23.83  XGBoost |
| **Skincare** | 33.99  Neural Network | 97.87  XGBoost | 127.95  Random Forest | 65.80  Neural  Network | 19.83  Neural Network |

***Table 5:*** *Periods-Category best results*

## 4.1 Summer Period

The summer period is based on the sales made during June 2019 to September 2019, which were all pre-pandemic sales. The results obtained during these times were quite good considering that only four months of the data were predicted. For this time period, the algorithm that obtained the best result was Random Forest with an RMSE as low as 1.67, obtained by the Mesotherapy category. This algorithm also performed best for three out of the six categories. For the Dermafiller category, the RMSE result obtained was 27.96 and the algorithm that performed the best was Random Forest Regression. Even though this category has the second highest number of sales in the data, the RMSE obtained is still not as high as some other categories. For the Needles category, the algorithm that performed the best was XGBoost with an RMSE of 1.98. The Profilho category obtained very high RMSE results compared to other categories, with an RMSE of 318.10, due to the extremely high number of sales. This category also tends to increase the growth of sales constantly, so the algorithm may not have performed the best due to this reason. Random Forest was the best algorithm for the Skinbooster category during the summer period with an RMSE of 33.95 which is neither the best, nor the worst. For the Skincare category, the best algorithm was Neural Networks with an RMSE of 33.99 which is very similar to the results obtained for the Skinbooster category.

## 4.2 Winter Period

The winter period is based on the sales made during October 2019 to December 2019, which were also all pre-pandemic sales. The results obtained during these times were also good considering that only three months of the data were predicted. For this time period, the algorithm that obtained the best result was XGBoost with an RMSE of 4.58, obtained by the Mesotherapy category. This algorithm also performed the best for four out of the six categories during the winter months. For the Dermafiller category during the winter period, the algorithm that performed the best was XGBoost with an RMSE of 24.26 which is very similar to the result obtained during the summer period. Neural Networks performed the best for the Needles category with an RMSE of 17.72, which is very high when compared to the result obtained during the summer period. For the Profilho category the RMSE obtained was 1320.98 by the XGBoost algorithm. This result was the highest RMSE from all the categories and also from all the time periods. This result may have been obtained poorly due to the reason that the pandemic having already started affecting some countries around the world and the purchasing of aesthetic products was not being considered a necessity. The algorithm that performed the best on the Skinbooster category was Neural Network with an RMSE of 51.87, which is considered satisfactory when compared to how the other algorithms performed on this category during this time period. XGBoost was the algorithm that performed the best on the Skincare category in this test data with an RMSE of 97.87.

## 4.3 Whole Year Period

The whole year period is based on the sales made between January 2019 and December 2019, which was the last pre-pandemic year. The predictions made during this period were also satisfactory since there were not any lockdowns present at that time yet. The lowest RMSE obtained for this data splitting was 3.93 obtained by the XGBoost algorithm for the Mesotherapy category. This algorithm performed the best for three out of the six categories during the 2019 year. For the Dermafiller category, the algorithm that performed the best was XGBoost with an RMSE of 97.84. This result is quite high when compared to the results of the other time periods obtained for this category excluding the covid year. The best RMSE result obtained by the Needles category was 15.65 and the algorithm that obtained this result was also XGBoost. This result was better than the result obtained during the winter period but not as good as the result of the summer period. For the Profilho category, the lowest RMSE obtained was 1103.03 by the Neural Network algorithm. This result was the second highest obtained result from the Profilho category following the winter period. This result shows that when the year 2019 was trained on the data between 2015 and the end of 2018, the sales did not reflect the past sales. The same reasoning applies for the Skinbooster and Skincare category as the RMSE is also considered a little high. For the Skinbooster category the best algorithm was Neural Network with an RMSE of 61.91 while for the Skincare category, the best algorithm was Random Forest with an RMSE of 127.95.

## 4.4 Covid-19 Period

## 4.5 Last 3 Months Period

## 4.6 Research questions results

To answer the research questions related to the pandemic period, the year during which multiple lockdowns in the UK happened, was used as testing data. The results obtained are shown in the tables below.

## 4.7 Comparing findings to previous studies

## 4.8 Additional findings

From the results gathered, it was also found that the sales started to increase again.

# Chapter 5: Conclusion and Recommendations

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# Appendices

**1.Summer Period**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **All Categories – Summer** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 699.14 | 488800.48 | 0.40 | 0.53 | 950.69 |
| XGBoost | 594.42 | 353333.23 | 0.57 | 0.61 | 811.06 |
| **Neural Network** | **452.28** | **204555.26** | **0.75** | **0.79** | **830.28** |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Jun 2019** | **Jul 2019** | **Aug 2019** | **Sept 2019** |
| **Actual** | 7164 | 6971 | 4878 | 6613 |
| **Predicted** | 6333.72 | 6875.05 | 5199.93 | 6486.43 |
| **Difference** | 830.28 | 95.95 | -321.93 | 126.57 |

Best Parameters:

* Random Forest:

Criterion: poisson

Max\_depth: 10

Max\_features: sqrt

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 5

Max\_features: log2

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: lbfgs

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Dermafiller – Summer** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| **Random Forest** | **27.96** | **781.67** | **0.77** | **0.77** | **49.17** |
| XGBoost | 42.16 | 1777.74 | 0.48 | 0.49 | 70.54 |
| Neural Network | 53.79 | 2893.14 | 0.16 | 0.20 | 84.72 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Jun 2019** | **Jul 2019** | **Aug 2019** | **Sept 2019** |
| **Actual** | 487 | 615 | 472 | 557 |
| **Predicted** | 484.82 | 565.83 | 490.07 | 576.18 |
| **Difference** | 2.18 | 49.17 | -18.07 | -19.18 |

Best Parameters:

* Random Forest:

Criterion: friedman\_mse

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 5

Max\_features: sqrt

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: lbfgs

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Mesotherapy – Summer** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| **Random Forest** | **1.67** | **2.79** | **-0.28** | **-0.25** | **2.48** |
| XGBoost | 2.21 | 4.88 | -1.23 | -1.20 | 3.17 |
| Neural Network | 3.14 | 9.83 | -3.49 | -1.57 | 6.14 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Jun 2019** | **Jul 2019** | **Aug 2019** | **Sept 2019** |
| **Actual** | 4 | 3 | 6 | 2 |
| **Predicted** | 5.37 | 3.43 | 3.52 | 3.72 |
| **Difference** | -1.37 | -0.43 | 2.48 | -1.72 |

Best Parameters:

* Random Forest:

Criterion: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 10

Max\_features: sqrt

Min\_samples\_leaf: 1

* Neural Network:

Activation: logistic

Solver: lbfgs

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Needles – Summer** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 2.00 | 3.99 | 0.72 | 0.86 | 3.41 |
| **XGBoost** | **1.98** | **3.93** | **0.72** | **0.83** | **3.51** |
| Neural Network | 4.80 | 23.05 | -0.62 | 0.66 | 6.71 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Jun 2019** | **Jul 2019** | **Aug 2019** | **Sept 2019** |
| **Actual** | 4 | 5 | 12 | 12 |
| **Predicted** | 3.32 | 3.51 | 12.84 | 8.49 |
| **Difference** | 0.68 | 1.49 | -0.84 | 3.51 |

Best Parameters:

* Random Forest:

Criterion: friedman\_mse

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* Neural Network:

Activation: tanh

Solver: adam

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Profhilo – Summer** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 517.28 | 267576.27 | 0.59 | 0.77 | 741.03 |
| XGBoost | 423.05 | 178973.35 | 0.73 | 0.75 | 565.15 |
| **Neural Network** | **318.10** | **101185.83** | **0.84** | **0.86** | **610.61** |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Jun 2019** | **Jul 2019** | **Aug 2019** | **Sept 2019** |
| **Actual** | 6046 | 5717 | 3940 | 5465 |
| **Predicted** | 5435.39 | 5813.70 | 4085.75 | 5428.94 |
| **Difference** | 610.61 | -96.7 | -145.75 | 36.06 |

Best Parameters:

* Random Forest:

Criterion: poisson

Max\_depth: 5

Max\_features: sqrt

Min\_samples\_leaf: 1

* XGBoost:

Criterion: squared\_error

Loss: huber

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* Neural Network:

Activation: identity

Solver: lbfgs

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Skinbooster – Summer** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| **Random Forest** | **33.95** | **1152.39** | **0.50** | **0.53** | **44.26** |
| XGBoost | 36.26 | 1315.07 | 0.43 | 0.46 | 51.16 |
| Neural Network | 58.23 | 3391.10 | -0.48 | 0.54 | 82.92 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Jun 2019** | **Jul 2019** | **Aug 2019** | **Sept 2019** |
| **Actual** | 342 | 245 | 212 | 272 |
| **Predicted** | 297.74 | 288.65 | 237.39 | 282.01 |
| **Difference** | 44.26 | -43.65 | -25.39 | -10.01 |

Best Parameters:

* Random Forest:

Criterion: friedman\_mse

Max\_depth: 5

Max\_features: sqrt

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 10

Max\_features: sqrt

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: adam

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| **Skincare – Summer** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 51.55 | 2657.21 | 0.09 | 0.85 | 73.15 |
| XGBoost | 76.29 | 5819.75 | -1.00 | 0.86 | 99.33 |
| **Neural Network** | **33.99** | **1155.26** | **0.60** | **0.74** | **57.96** |

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|  | **Jun 2019** | **Jul 2019** | **Aug 2019** | **Sept 2019** |
| **Actual** | 287 | 386 | 236 | 305 |
| **Predicted** | 252.95 | 328.04 | 238.27 | 314.88 |
| **Difference** | 34.05 | 57.96 | -2.27 | -9.88 |

Best Parameters:

* Random Forest:

Criterion: poisson

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: quantile

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: adam

**2.Winter Period**

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| **All Categories – Winter** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 1792.80 | 3214142.17 | -11.64 | 0.46 | 2136.78 |
| XGBoost | 1610.31 | 2593089.41 | -9.20 | 0.49 | 1899.85 |
| **Neural Network** | **457.41** | **209220.28** | **0.18** | **0.46** | **711.11** |

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|  | **Oct 2019** | **Nov 2019** | **Dec 2019** |
| **Actual** | 8819 | 8492 | 7624 |
| **Predicted** | 8107.89 | 8684.05 | 7332.28 |
| **Difference** | 711.11 | -192.05 | 291.72 |

Best Parameters:

* Random Forest:

Criterion: squared\_error

Max\_depth: 10

Max\_features: sqrt

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: huber

Max\_depth: 10

Max\_features: sqrt

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: lbfgs

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| **Dermafiller – Winter** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 93.22 | 8690.51 | 0.23 | 0.77 | 142.54 |
| **XGBoost** | **24.26** | **588.44** | **0.95** | **0.95** | **34.59** |
| Neural Network | 97.11 | 9430.14 | 0.16 | 0.16 | 135.06 |

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|  | **Oct 2019** | **Nov 2019** | **Dec 2019** |
| **Actual** | 731 | 809 | 555 |
| **Predicted** | 722.10 | 774.41 | 577.12 |
| **Difference** | 8.9 | 34.59 | -22.12 |

Best Parameters:

* Random Forest:

Criterion: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* XGBoost:

Criterion: squared\_error

Loss: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: lbfgs

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| **Mesotherapy – Winter** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 5.60 | 31.33 | -0.20 | 0.19 | 9.65 |
| **XGBoost** | **4.58** | **20.93** | **0.19** | **0.47** | **7.91** |
| Neural Network | 5.81 | 33.76 | -0.30 | 0.15 | 9.90 |

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|  | **Oct 2019** | **Nov 2019** | **Dec 2019** |
| **Actual** | 14 | 5 | 2 |
| **Predicted** | 6.09 | 5.32 | 1.57 |
| **Difference** | 7.91 | -0.32 | 0.43 |

Best Parameters:

* Random Forest:

Criterion: poisson

Max\_depth: 5

Max\_features: sqrt

Min\_samples\_leaf: 2

* XGBoost:

Criterion: squared\_error

Loss: huber

Max\_depth: 5

Max\_features: sqrt

Min\_samples\_leaf: 1

* Neural Network:

Activation: logistic

Solver: adam

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| **Needles – Winter** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 30.96 | 958.77 | -0.14 | 0.23 | 53.63 |
| XGBoost | 32.36 | 1047.10 | -0.25 | 0.15 | 56.03 |
| **Neural Network** | **17.72** | **314.10** | **0.63** | **0.71** | **30.43** |

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|  | **Oct 2019** | **Nov 2019** | **Dec 2019** |
| **Actual** | 4 | 65 | 3 |
| **Predicted** | 7.91 | 34.57 | 4.00 |
| **Difference** | -3.91 | 30.43 | -1 |

Best Parameters:

* Random Forest:

Criterion: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 10

Max\_features: sqrt

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver': adam

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| **Profhilo – Winter** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 1443.81 | 2084586.86 | -10.25 | 0.76 | 1639.44 |
| **XGBoost** | **1320.98** | **1744994.71** | **-8.42** | **0.57** | **1630.13** |
| Neural Network | 1376.40 | 1894477.23 | -9.23 | -0.28 | 1959.08 |

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|  | **Oct 2019** | **Nov 2019** | **Dec 2019** |
| **Actual** | 7337 | 6611 | 6312 |
| **Predicted** | 5706.87 | 5668.65 | 5012.15 |
| **Difference** | 1630.13 | 942.35 | 1299.85 |

Best Parameters:

* Random Forest:

Criterion: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 1

* Neural Network:

Activation: identity

Solver: lbfgs

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| **Skinbooster – Winter** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 95.15 | 9053.49 | -4.07 | 0.85 | 115.47 |
| XGBoost | 105.61 | 11154.25 | -5.25 | 0.77 | 128.05 |
| **Neural Network** | **51.87** | **2690.48** | **-0.51** | **0.85** | **65.52** |

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|  | **Oct 2019** | **Nov 2019** | **Dec 2019** |
| **Actual** | 369 | 405 | 303 |
| **Predicted** | 313.50 | 339.48 | 276.56 |
| **Difference** | 55.5 | 65.52 | 26.44 |

Best Parameters:

* Random Forest:

Criterion: poisson

Max\_depth: 5

Max\_features: sqrt

Min\_samples\_leaf: 1

* XGBoost:

Criterion: friedman\_mse

Loss: squared\_error

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: adam

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| --- | --- | --- | --- | --- | --- |
| **Skincare – Winter** | | | | | |
| **Algorithm** | **RMSE** | **MSE** | **R^2** | **Explained Variance** | **Max Error** |
| Random Forest | 146.18 | 21369.34 | -1.31 | 0.08 | 236.12 |
| **XGBoost** | **97.87** | **9578.92** | **-0.03** | **0.16** | **160.44** |
| Neural Network | 249.76 | 62380.59 | -5.73 | -0.05 | 363.33 |

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| --- | --- | --- | --- |
|  | **Oct 2019** | **Nov 2019** | **Dec 2019** |
| **Actual** | 364 | 597 | 449 |
| **Predicted** | 415.65 | 436.56 | 430.85 |
| **Difference** | -51.65 | 160.44 | 18.15 |

Best Parameters:

* Random Forest:

Criterion: poisson

Max\_depth: 5

Max\_features: log2

Min\_samples\_leaf: 2

* XGBoost:

Criterion: friedman\_mse

Loss: quantile

Max\_depth: 10

Max\_features: log2

Min\_samples\_leaf: 2

* Neural Network:

Activation: identity

Solver: lbfgs

1. https://www.ons.gov.uk/economy/grossdomesticproductgdp/articles/gdpandeventsinhistoryhowthecovid19pandemicshockedtheukeconomy/2022-05-24#:~:text=The%20COVID%2D19%20pandemic%20prompted,country%20reopened%20over%20the%20summer. [↑](#footnote-ref-1)