Sales Optimization Solution for Fashion Retail

N.B.Ganhewa
Department of Software Engineering and Computer Science
Sri Lanka Institute of Information Technology
Kandy, Sri Lanka
nimaya.bg@gmail.com

S.M.L.B.Abeyratne
Department of Software Engineering and Computer Science
Sri Lanka Institute of Information Technology
Kandy, Sri Lanka
lakminaabeyratne56@gmail.com

G.D.S.Chathurika
Department of Software Engineering and Computer Science
Sri Lanka Institute of Information Technology
Kandy, Sri Lanka
gallegesupuni@gmail.com

Dilani Lunugalage
Department of Software Engineering and Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
dilani.l@sliit.lk

Dilshan De Silva
Department of Software Engineering and Computer Science
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka
dilshan.i@sliit.lk

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***Abstract*—The Fashion industry is one of the extensive, changeable, and growing businesses to exist. It encompasses fashion retailing which functions as a mediator between the manufacturers and clients. On account of the inconsistency of this industry, maximizing sales has been a crucial task. The objective of this research study is to analyze and explore product and consumer behavior and thereby maximize sales in the fashion retail industry for women's clothing to overcome the struggles regarding gaining sales confronted by the industry. The emergence of big data and machine learning has a positive influence on fashion retailing. ML has been utilized in this research to implement a web application that aids in optimizing sales. It comprehends sales forecasting, customer segmentation, and customer demand analytics. Each research component obtains diverse inputs to initialize the prediction and visualization procedure. The models are built employing the Extra Trees Regressor algorithm, K-means algorithm, and Naïve Bayes algorithm. Finally, for specified inputs, results will be predicted that comprise sales forecasts for products, segmentation of consumers, and forecasts about most demanded fashion item's characteristics. This paper portrays the proceedings of data preparation, model development, and results of each research component.**

Keywords*—Fashion retail, Machine learning, Sales forecast, Customer segmentation, Extra Trees Regressor, K-means algorithm, Naïve Bayes algorithm

I. Introduction

Contemporarily, clothing is viewed more than as a means of meeting a necessity. It is also a form of self-expression, personal taste, and cultural relevance in the modern era. The fashion industry represents the constant shift in human desire on a daily basis. The fashion industry is now a 1.3 trillion-dollar venture committed to the business of designing, manufacturing, retailing, and marketing clothes.

Fashion retailing operates as a middleman between manufacturers and consumers, purchasing fashion goods from manufacturers and reselling them to customers. Within the past decades, the fashion retailing business has grown on a large scale. Some of the highlights in this progression are the beginning of local markets where a small amount of clothing was sold and the evolution into department stores with mass productions, expansion of retail through localization and internationalization, and with the appearance of the internet, the high utilization of e-commerce was established which paved the way for many consumers to purchase clothing online from diverse countries.

A retail business's stability and the opportunity for growth are simply determined by how well sales are performed. With regard to this retail industry numerous elements influence sales. Competitiveness is a key factor in this industry which emerges through high volatility and demand. Human desire varies according to many aspects. This changeability offers many retailers the opportunity to distribute diverse merchandise. However, obtaining profits in this state of circumstances is a genuine challenge.

The problem is that, because fashion retail is such a fickle sector, garnering sales is considerably more difficult. Some specific challenges the fashion retail industry encounter are as follows, the frequent shift of fashion trends, the short shelf life of some fashion goods, excessive volatility of consumer demand, Existence of a vast consumer group.

It is challenging to optimize sales in fashion retail with such fast fluctuations in demand. If these obstacles aren't tackled in the right way, it will result in under-stocking and over-stocking, inability to understand and meet the consumer requirements, incompetent capital management, and etc. The research problem undertaken in this study concerns how retailers can maximize sales by overcoming these overwhelming challenges.

The primary objective of this research study is to implement a web application that will assist in optimizing sales in the fashion retail industry for women's clothing with a higher customer satisfaction level by foreseeing product and consumer behaviour. To accomplish the primary objective this research study was carried out under three research components which comprise sales forecasting, customer segmentation, and customer demand analytics.

Optimizing sales can be addressed using different approaches however in this research study ML methods have been utilized to achieve this goal. Because of decisions made by humans tend to be less reliable automated approaches were utilized more and more in this industry. ML has been extensively applied in the retail industry since it provides promising predictions and pattern recognition outcomes.

Sales forecasting mechanism permit retail businesses to accurately administer inventory which assist in increasing sales while managing a standard profit. Absence of a legitimate plan in the business will embark on drawbacks such as higher inventory levels, lost orders, failure to meet customer demand and etc. Sales forecasting procedures can overcome these drawbacks productively. With the high volatile elements that influence fashion product sales, having precise predictions has been critical. Initially, conventional statistical approaches were used to enforce sales forecasting. With the expansion of the retail market the concept of mass production was introduced. Therefore, a significant number of diverse elements began to impact a large amount of data. For that reason, this large amount of data may not satisfy linear relationships, resulting in estimates that are inaccurate. Therefore, to obtain accurate sales projections ML algorithms were utilized in this research study. The objective of this research component is to attain accurate future sales predictions by analysing the ever-changing factors that affect women's clothing sales. This process will authorize retail businesses to manage inventory for future advancement of sales.

Since there is a vast consumer group in this industry, difficulty of identifying every customer's needs increases as well. Inability to handle this drawback will decline sales. In this research study, we have used customer segmentation to address the above issue. This aids in target marketing. Targeted marketing for groups with similar patterns will drive for more purchases and impulse buys which will result in sales maximization. In this research, customer behaviours are analysed, and customers are segmented into groups with similar characteristics based on several features. This research component will be helpful for retailers to easily segment their customers and will assist them for better business sales by target marketing and to make correct business decisions.

Customer demand analysis is a thorough investigation into which fashion goods are demanded mostly by customers by examining the customer purchases and reviews. As a result, on a given dataset, we do an extensive analysis of sold items, which comprises consumer buying rates and consumer reviews. These features are firmly analysed which results in revealing client preferences in purchasing fashion items. The consumer reviews are divided into positive and negative categories which bring out customer satisfaction levels about the purchase. We can determine the most desirable colour, dress type, price, and size based on the findings of this analysis. Finally, items that are mostly reviewed positively can be recommended by the recommendation model. This proposed solution will permit retailers to heighten sales by meeting the consumer prerequisites in a proficient way.

This research study has exploited a variety of ML algorithms to optimize sales in the fashion retail industry with the inspection of a significant number of changeable input elements to attain accurate predictions and patterns which will benefit retail managers regarding decision making on sales and customer demand.

II. Literature Review

Several sales forecasting research studies have been done over the past few years with overcoming different drawbacks regarding the research. Initially, people utilized traditional statistical methods to achieve this. With mass predictions and diverse factors affecting sales, to gain more accuracy researchers used ML methods to implement sales forecasting which has the ability to identify nonlinear relationships between features.

The research handled by K. F. Au et al [1] proposed the evolutionary neural network (ENN) for the fashion sales forecasting model. They reached the conclusion that the model suggested is for fashion products with uncertain seasonal patterns and low demand, and that it outperforms the classic statistical approach SARIMA method in terms of performance.

Z. L. Sun et al [2] have used Extreme Learning Machine (ELM) to forecast sales in fashion retail. Training data and the testing data in this dataset were normalized. The relationship between the number of sales and the symbolic characteristics that influenced sales, such as colour, size, and price, was explored using this model. However, ELM is not the most reliable method because the results vary from run to run.

C. Frank et al [3] use two methods to implement sales forecasting for women's fashion retail which are artificial neural networks (ANNs) and statistical time series modelling. The feed-forward back propagation technique was modelled in this study. This methodology looked into the seasonality of fashion products. The dataset of past sales of fashion items comprised of training data, testing data, and data to compare results. The contrast between the projections and the actual sales data was not satisfactory, while R^2 performed admirably.

Many researchers conducted studies under customer segmentation using ML algorithms. Almost many of the research studies have used the K-means clustering algorithm to achieve this objective.

In this research study [4] K-means technique is trained using a 2-feature dataset of 100 training patterns. The average amount of items purchased per month and the average number of customer visits per month are the 2 features. To obtain results 4 major steps were followed. Feature normalisation that converts all data items to a similar scale to improve the clustering algorithm's performance. Each data point is assigned to the cluster whose centroid yields the least within-cluster sum of squares when compared to other clusters during the assignment stage. Finally, after each iteration, a new centroid is generated for each cluster as the mean of the data points in the cluster until the cluster centroids become stable. Four consumer categories were determined as a result with a 95% accuracy.

This study [5] emphasizes the notion of utilizing density-based algorithms like the DBSCAN algorithm for consumer segmentation, in addition to using centroid-based algorithms like k-means. A wholesale consumer dataset that comprises information on a wholesale distributor's clients' annual spending and statistics on their consumption of various products. Unlike k-means, however, DBSCAN offers an extra alternative to locate unique customers with different purchase habits that are very productive to ensure customer pleasure and optimum benefit, according to the report.

There are plenty of research studies done regarding the fashion industry but very few of them are done concerning customer demand analysis on fashion items. When we consider the few studies done under customer demand analysis on different industries, they use historical data of customer behaviour to analyse customer demand using ML techniques.

The research held by A. O. Gladys et al [6] have attempted to forecast demand for coloured fashion goods in the industry. They have utilized convolutional neural network and K-means algorithms to achieve this objective. Initially, they used the convolutional neural network for the model by obtaining underlying details from the image collection which they gathered from a variety of events. The details extracted were then used in conjunction with the K-means algorithm to cluster the collected images into numerous distinct colour segments in the order of supremacy. The training and validation accuracy in this model was 89.9% and 87.5% respectively. This model can be valuable when it comes to production planning by factoring the future desires of colours.

In this selected research [7] they have predicted demanded suppliers from consumer orders which involved product features as well. They attempt to forecast the best supplier for a new order from a customer. They applied data mining methods and classification algorithms which are, K nearest neighbour (KNN), Random Forest (RF), Neural networks (NN), and Naïve Bayes (NB) to implement the model and depicted the most suitable model to address this problem. They concluded that RF and NN models displayed consistent performance and higher accuracy. With the complex behaviour of customized fashion product orders by customers this process aids in making an automated decision. Since this study was done on a small dataset some limitations occurred during the process. It can be conquered by enhancing the parameters along with the size of the dataset.

III. Methodology

In this section we confer about the mechanisms used for this research which is a system for machine learning based sales optimization. This research study comprises of three research components which are sales forecasting, customer segmentation, and customer demand analytics. According to past product and consumer behaviour this system will assist in maximizing sales. Each component has utilized diverse machine learning algorithms and techniques to accomplish each objective. It encompasses prediction and visualization.

A. Sales Forecasting

The sales forecasting component utilizes an ensemble learning method called Extra Trees Regressor to implement the proposed model. The data collected will be analysed and the most dominant factors that affect sales will be designated as the inputs of the model. The predicted sales quantity will be the targeted output. In this section, each step of this process will be elaborated.

The dataset used for this prediction are features of summer-associated fashion products which come from the wish service platform. It contains information such as design factors, product ratings, prices, and sales performance from 2020 July. This dataset persists 1537 women's summer fashion products with 43 features for each product. The sales quantity is the target variable in this process.

*1) **Data Pre-processing:*** Preprocessing the data before delivering it to the model is the foremost step. This process includes deriving convenient features that affect target output and altering the data to a state that a machine learning algorithm can parse.

a) Cleaning the data: The main purpose of this step is to provide quality data to increase the productivity of the model. In this dataset to clean the data, several steps were executed. Initially, the columns with images were dropped since we are evaluating statistical data. The columns that provide similar meaning as in duplicate columns, columns that consist of one unique value, and columns with very few value counts for distinct values except for one value were also dropped. Then the null values were handled by altering them with the most value count items. Few columns had values that had a similar meaning in diverse interpretations. It was handled by combining values such as entering one value to represent every similar value within the column.

b) Exploratory data analysis (EDA): EDA is primarily used to visualize data in order to have a better knowledge of data distributions of the dataset and to determine the correlations between variables. This method allows the chance for visual analysis of data. Using a heatmap we observed the correlation between features and the target variable. Few columns with minimum correlations were dropped in this process. Then we visualized each attribute by using scatter graphs and bar charts.

c) One hot encoding: Labels are used to create categorical data. In ML, the models must be fed with numerical values to train and the outputs should be numerical as well since they are mathematical models. As a result, categorical data must be pre-processed to handle them in a model. So the categorical data in this dataset must be encoded into numeric data before being used to train the model. There are two preferred encoding approaches. Which are one-hot encoding and ordinal encoding. In this component, the one hot encoding method has been applied to convert categorical data. The reasoning behind this selection is that the categorical data in the collected dataset are nominal variables, meaning they are made up of independent categories with no relationship to each other. Ordinal encoding allocates integer values to each unique category in the selected attribute which may lead the model to believe that a relationship may exist between them when there is not. This could result in poor performance and erroneous outcomes. To avoid this, one hot encoding was utilized. For each unique category in the original column, it will create a new binary attribute.

d) Removing outliers: Outliers have the ability to distort statistical evaluations and escalate the error variance in predictions. In this research component, the Grubbs test function was used to detect outliers. The Grubbs test initially, will calculate the G test statistic then, calculate the G critical value using a formula finally it will compare the G test statistic and the G critical value and detect an outlier if the G critical value is less than the G test statistic. After the detection, the outliers will be removed.

$$G = \frac{\max_{i=1...N} |Y_i - \bar{Y}|}{s} \quad (1)$$

e) Feature scaling: Through feature scaling all independent features' range will be normalized. As the algorithms can be sensitive to the distance of data points. This process will make the training fast. In this process, a StandarScaler was used to achieve this. This scaling is done in terms of features. Standard scaling can be impacted by outliers so the outliers were removed beforehand as well. By this scaling, the distribution of data will have a standard deviation of 1 and a mean of 0. The distributions of features of before and after scaling were illustrated using Kernel Distribution Estimations (KDE) plots.

*2) **Training the Model:*** After pre-processing the dataset the dominant variables that affect the sales performance of these products were identified. They were fed to the model as inputs to get accurate predictions. Training a model includes the following steps.

a) Training and testing data: Splitting the dataset into training and testing data can be helpful to evaluate the performance of the model. The training dataset prepares the model to train by analyzing and identifying hidden patterns. The dataset in this component was split into train and test with 80/20 respectively.

b) Extra Trees Regressor: This algorithm is an ensemble of decision trees algorithms combined. It executes a meta estimator that is able to fit a great number of randomized not pruned decision trees on numerous subsets of the dataset. By averaging the predictions of each decision tree, the final regression predictions will be constructed. Although this algorithm selects the point where it splits nodes randomly in the end the algorithm will choose the finest point out of all which adds randomization as well as optimization to this algorithm. The execution time is much faster than the random forest algorithm. In this component, the model was initialized with the algorithm using the scikit-learn library. And the training dataset which includes the most supreme features that affect sales quantity was fed in order to train the model and to get more accurate predictions of sales.

c) Model testing: Finally, the trained model was tested and the forecasted sales quantities were compared using the testing dataset with the utilization of diverse performance metrics.

B. *Customer Segmentation*

The dataset analysed in this research component consists of 24 attributes and 2823 tuples that represent customer behaviour. The 24 attributes include Sales, Price, Quantity, Status, Month, Year, MSRP, customer name, phone, city and etc. The initial phase of the research is data cleaning and as the first step of cleaning data columns with the null values such as address line 2, state, postal code, and territory were dropped. Also, City, Address line 1, Phone number, and customer name were dropped as well since they are not required for the analysis.

As the next step to get a clear understanding of the data distributions, visualization was done. This visualization was achieved with the use of bar plots which depict the count of each value in an attribute.

Then the categorical data were handled in order to prepare data that can be fed to the model. It includes encoding categorical variables. Here the Status attribute persists 6 categories which are shipped, cancelled, on hold, disputed, in process, and resolved were encoded with ordinal encoding which assigned integers for each category. Then the other remaining categorical variables such as product line, deal size, and country were converted into dummy variables using one-hot encoding approach.

Then the relationship between the order date attributes and sales were visualized using a KDE plot. After the observation of the KDE day of the order date were dropped since the relationship was weak and the month and year of the date were kept.

Then a correlation matrix is used for the remaining features to demonstrate the correlation between the features. After careful consideration of each relationship between features, the weakly correlated features were dropped since they do not have much impact on the process. Then the final pre-processed dominant features were visualized using distribution plots to get a better understanding of the inputs.

K-means algorithm - K-means algorithm was used to achieve the clustering in this research component. It is an unsupervised learning algorithm that partitions unlabelled data into k distinctive clusters such a way that each cluster include similar characteristics. Each cluster will get appointed a centroid and the intention of the algorithm is to reduce the total distances between the centroid and the points. It can easily assemble clusters with different shapes with the assurance of convergence.

As shown in Fig. 1 below the elbow method is applied in the k-means algorithm to find the optimal number of clusters. This method will compute the total of the square of the points and will compute the average distance. When the value of k is 1 the within-cluster sum of the Square (WCSS) will be higher. The output k is nearly equal to 5 in this component therefore 5 clusters will be considered.

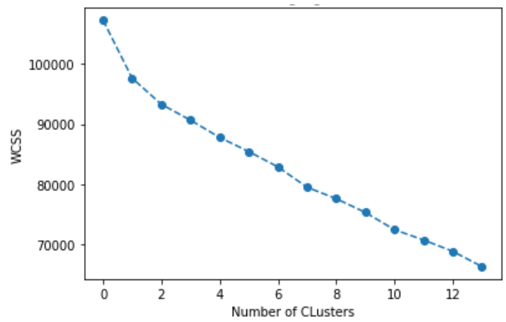

Fig. 1. Usage of the elbow method

With the application of the model, customers were segmented as the output. It produced 5 clusters regarding consumers as the outcome. Then to get a clear understanding of the clusters, histograms were used for each feature based on the cluster. And the results of segmented clusters were visualized using diverse methods.

Finally, again customers were segmented into clusters using only 2 features. The 2 features were sales and status of the order. This segmentation was done to ease the decision-making process of the client. In this segmentation, 9 clusters were identified.

C. *Customer Demand Analytics*

The proposed customer demand analysis research component consists of 9 steps as follows.

1. Loading the data – Initially, the data set is imported. The dataset persists consumer details, purchased item details, and reviews regarding the purchase.
2. Checking and handling missing values in the dataset.
3. Cleaning the data - Afterwards few columns are dropped which does not consist of proper item details or proper reviews.

In this component, after data preparation, there are two main procedures which are data visualization and model implementation with the usage of ML.

4. Data analysis and visualization - The data visualizations are done using histograms, scatter plots, and boxplots. Using those diagrams, we can

identify mostly purchased items in reference to colour, age group, dress type, size, ratings, etc. Different characteristics of the dataset are compared with each other to analyse and visualise customer purchasing pattern with age, colour, size, etc. Then customer reviews are analysed and visualized with consumer details as well to observe details regarding demands.

Then text data in reviews are cleaned which include repeated words and then the polarity of the reviews which means the positivity or negativity of the reviews will be recognized.

TextBlob python library is used to proceed with a sentiment analysis using naive Bayes classification. Sentiment Analysis can assist us in determining the mood and feelings of the general public as well as obtaining useful information about the setting. Sentiment Analysis is the process of assessing data and categorizing it according to the research's needs. When considering TextBlob it is a Natural Language Processing (NLP) python package. Natural Language Toolkit (NLTK) was used extensively by TextBlob to complete its objectives. NLTK is a library that allows users to work with categorization, classification, and a variety of other tasks by providing easy access to a large number of lexical resources.

The polarity and subjectivity of a statement are returned by TextBlob. In here the range of polarity is between -1 and 1. If the polarity is less than 0 it indicates negative sentiment, if it is 1 it indicates a positive sentiment and if 0.5 it indicates a neutral review.

Also using TextBlob we can break words into decimal values and polarity can be identified by using an algorithm. polarity graph is drawn with the use of its decimal values and then department name and polarity are depicted as a boxplot.

Then review length and the review text number of tokens are counted and they are illustrated using histograms. With the use of all the evaluated details regarding reviews a pie chart indicating negative, positive, and neutral reviews will be presented as shown in the Fig. 2.

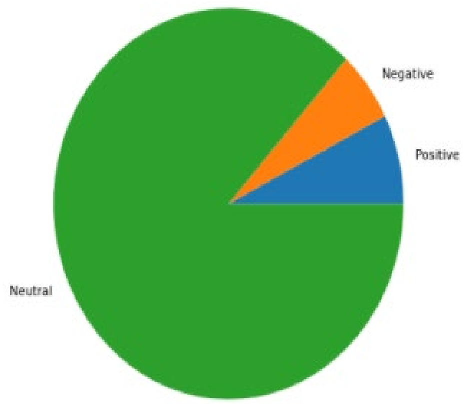

Fig. 2. Evaluations distributed in a pie chart

Then texts are counted in unigram, bigrams, and trigrams using the countvectorizer tool. It is used to convert a text into a vector-based on the frequency of each word that appears throughout the text. In this process words which has close meanings are stopped.

Next, a heat map was used to get a better understanding of the correlation between evaluated features.

5. Handling Multicollinearity – The review length is compared with the token count. Then the features are compared with each other and visualized in diagrams to view the comparison. The positive feedback count with diverse affected features will be compared.

Then the implementation of models will be initiated. In this component, 3 machine learning models will be implemented including a deep learning model. And compare all the models to find the model with the highest accuracy. For ML models Naive bayes algorithms are used along with two techniques which are the bag of words and Term Frequency-Inverse Document Frequency (TF-IDF) Technique.

6. Building ML model using Bag of words - Bag of words is a technique for extracting features from text sources. ML algorithms can be trained using these features. It develops a vocabulary of all the unique words found in the training set's papers. Bernoulli Naive Bayes algorithm used for discrete data. Its key feature is that it only accepts binary values for features.
7. Building ML model using TF-IDF Technique - The TF-IDF statistically examines how much is a word to a document in a collection of documents. It increases in proportion to the number of times a word appears in a document but is countered by the number of papers that contain the word. Multinomial Naive Bayes algorithm is used for this model. This algorithm is a probabilistic learning approach popular in NLP. It guesses the tag of a text, such as an email or a newspaper story, using the Bayes theorem. It calculates each tag's likelihood for a given sample and outputs the tag with the highest probability.
8. Deep Learning Model with Embeddings - Finally Deep learning model is created. In here tokenization algorithm is used by TensorFlow. Tokenization is one of the foremost processes in NLP, and it entails breaking down a string of text into semantically meaningful units. Tokens are these units, and the issue in tokenization is determining the optimal split so that all tokens in the text have the same meaning and no tokens are left out. In this step, embedding is also done. Word embeddings are a sort of word representation that allows the illustration of words with comparable meanings. They are a distributed representation for the text that may be one of the main breakthroughs in deep learning approaches' excellent performance on difficult NLP issues.

IV. RESULTS & DISCUSSION

A. Sales Forecasting

Initially, with the testing dataset, the sales quantity was predicted using the model. The forecasted values were compared with the test values as shown in Table I.

Table I. Comparison between the actual and predicted values

Test Sales Values	Predicted Sales Values
10000.0	7196.847080
100.0	100.000000
1000.0	885.162345

With the usage of performance metrics, the model was evaluated. The model presented satisfactory results with the metrics Mean Squared Error (MSE), Root Mean Square Deviation (RMSE), and Mean Absolute Error (MAE).

Table II. Performance metrics

MSE	1.263030982379541
RMSE	1.1238465119310292
MAE	0.72

B. *Customer Segmentation*

As a result of applying the K-means algorithm to the dataset 5 clusters were identified. These clusters have specified characteristics that are unique to them.

CLUSTER 0 - Total Quantity, total price, shipped orders, and total MSRP are high. Total sales, no of customers active in all months, and no of customers active in 2003-2005 are between high-medium.

CLUSTER 1 - Total quantity, total price, total sales, shipped orders, no of customers active in all months, no of customers active in 2003-2005, and total MSRP are high.

CLUSTER 2 - Total Quantity, total price, total sales, shipped orders, no of customers active in all months, no of customers active in 2003-2005, and total MSRP are low.

CLUSTER 3 - Total Quantity, price, sales, and shipped orders, no of customers active in all months, no of customers active in 2003-2005, and total MSRP are between low-medium.

CLUSTER 4 - Total Quantity, price, sales, shipped orders, no of customers active in all months, no of customers active in 2003-2005, and MSRP are medium.

To visualize the clusters clearly Principal Component Analysis (PCA) was applied as shown in Fig. 3. PCA reduced the 8-feature dataset to a 3-feature dataset and visualize the clusters clearly. This Dimensionality Reduction method aids in getting a better idea about the clusters.

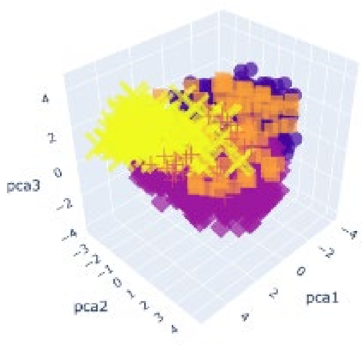

Fig. 3. Segmented clusters visualization

Then 9 clusters were evaluated for the second clustering with the usage of 2 features and were illustrated using a scatter plot.

C. *Customer Demand Analytics*

In the data visualization part, we can identify mostly purchased items and positively reviewed patterns using various diagrams. When it comes to purchasing items mostly it was customers between the age group of 30-40. Dresses were the most purchased fashion product.

When the models were created, the ML model with the Bag of words technique had higher accuracy. But when the deep learning model was created it presented higher accuracy than the other 2 conventional ML techniques and in the given dataset it was 0.99.

V. CONCLUSION

This paper presents an improved sales optimization solution for fashion retailing with the utilization of ML. The proposed mechanism delivers sales forecasts of fashion products, customer segmentation which helps in targeted marketing and predicts consumer demands based on products reviews. Sales forecasting was achieved with the use of an extra trees ensemble learning method, customers were segmented based on similar characteristics using the k-means algorithm, and the customer demand was visualized and predicted using 3 machine learning algorithms. The research study demonstrated satisfactory results in each research component. This proposed solution was intended to be used by retail managers in order to help the decision-making process to maximize sales in the fashion industry since it is a very volatile and competitive industry. Further studies can be done in order to enhance this solution. Rather than targeted marketing as the next step, personalized marketing will have more potential in the near future.

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