A study on reviews of online grocery stores during COVID-19 pandemic using sentiment analysis

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Abstract: Digitalisation is playing a very crucial role in India during the COVID-19 lockdown. Grocery items are one of the essential commodities needed by the people during the lockdown. The sales of online grocery stores rose abnormally during the pandemic and stores faced a lot of problems while delivering grocery items to consumers. It becomes very difficult for them to deliver the products on time and maintain the satisfaction level of the consumes. During that time, huge online reviews were posted by consumers on different digital platforms. This study focussed on analysing those reviews and developing a supervised machine learning model. Sentiment analysis is used to develop the classification model. TF-IDF followed by naïve Bayes classification techniques is used to do the sentiment analysis. The developed model helps the online grocery stores to deal with huge online reviews and segment the consumers based on their positive and negative reviews.

Keywords: sentiment analysis; naïve Bayes classification; TF-IDF; online grocery stores; pandemic.

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1 Introduction

In the last ten-year buying behaviour of consumers has changed tremendously. In the present digitalised world, consumers are moving from the physical marketplace to the digital market space (Ismagilova et al., 2020). In India, cheap internet services accelerated the growth of online purchasing and attracting consumers. Online shopping is convenient for consumers. In todays rush life, consumers want grocery items at their doorstep. Internet revolution in India has penetrated every sector; online shopping is also untouched (McCole et al., 2010). Electronic commerce has a significant impact on the purchasing behaviour of consumers. Online grocery stores emerge as competitors of grocery stores. Online stores are also facing significant challenges (Hassanein and Head, 2007). COVID-19 pandemic has changed the purchasing intentions and buying behaviour of the consumers (Bag et al., 2021a). Unexpected consumer behaviour was observed during the lockdown. Pandemic has changed the way of purchasing to a great extent. It has impacted grocery stores and consumers switched towards online grocery stores. Consumers had started panic buying which created new challenges for grocery stores. Grocery items are essential for every household (Laato et al., 2020). The buying pattern of consumers has changed during the pandemic. Analysing the buying behaviour pattern of consumers is a complicated task. Online grocery stores have a significant impact on purchasing behaviour. Due to panic buying, most of the online grocery stores were facing the problem of supply shortage. During the pandemic, the role of online grocery stores become very crucial, they were supplying the products at the doorstep of consumers by maintaining social distancing (Naeem, 2021). Grocery items are essential for any household, so people started impulse buying during COVID-19 (Arafat et al., 2020). Retailing activities significantly changed during the pandemic and it impacted consumer behaviour as well. Long waiting queue and shortage of products has significantly impacted the supply chain and caused disruption. It had also repercussions on consumer behaviour but the impact of the pandemic on the consumers of an online grocery store is missing (Pantano et al., 2020). Food app delivery plays an important role in China during the pandemic to fulfil the grocery demands of the consumers. Customer satisfaction is the most significant factor during a pandemic in China and perceived required technology, expected performance and social factors have an indirect impact on the consumers who use food app delivery (Zhao and Bacao, 2020). India has the second-largest population after China, so a study is needed in the Indian context.

Artificial intelligence is infiltrating all facets of business and marketing. It is become critical for marketers and retailers to use digital information to have a deeper understanding of their customers' purchasing habits. The automated decision support system improves a decision maker's ability to make a rapid and precise decision (Ma and Sun, 2020; Bag et al., 2021b).

Artificial intelligence might be used to translate customer online reviews into relevant data that retailers and marketers can use to make better decisions (Bag et al., 2021c). The online platform gives detailed information on the consumers, which reduces ambiguity. Sentiment analysis could be used to create a model that predicts customer purchasing habits (Fan et al., 2017). COVID-19 pandemic has changed consumer purchasing behaviours. Customers nowadays prefer to buy products online. Instead of going to the store, the store is now coming to the consumers' homes. New habits are arising in consumers as a result of demographic shifts, technological innovation, and consumers' dynamic cognitive behaviour (Sheth, 2020). During the COVID-19 outbreak, online grocery shop sales soared dramatically. Consumers did not want to go outside to buy groceries. There is fierce rivalry among online grocery stores to meet the needs and expectations of customers. A study is required to learn about consumer feedback to comprehend consumer expectations for online grocery shops selling perishable agricultural items, which will assist grocery businesses in improving their services. Hence:

RQ1 How do reviews of the consumers help the online grocery stores to improve their services?

Customers' online reviews can be used to generate big data that can be turned into useful information. The monitoring and analysis of these massive quantities of data improve decision-making. A big data-based machine learning model assists the manager in making the best decision and enables predictive analysis. Sentiment analysis is one of the best tools for developing an integrated framework based on big data (Kauffmann et al., 2020). Sentiment analysis is one of the most important tools to evaluate online reviews. Extraction of reviews is widely used to know the sentiment of the consumers (Hu et al., 2012). Rare research has been conducted to analyse the reviews of the consumers towards online grocery stores. Online reviews of consumers have a significant impact on buzz marketing. It affects the performance of the business (Ye et al., 2009). In the era of digitalisation, grocery stores are transforming themselves into online grocery stores (Lagorio and Pinto, 2020). It becomes crucial for them to understand the feedback of the consumers to improve their services. So, a study is needed to analyse the reviews of the consumers towards online grocery stores. Hence:

RQ2 How to develop the supervised machine learning model to deal with huge online reviews given by consumers?

Due to COVID-19, the buying behaviour of consumers has changed. Now, consumers do not prefer to go to the shop physically. They prefer to do shopping through the online platform (Sheth, 2020). COVID-19 caused several disruptions in the business of online grocery stores. A study is needed to understand the buying behaviour pattern of the consumers by analysing online reviews. Online grocery stores need to be more competitive to attract customers. Communication is an important factor that online grocery stores should consider to retain consumers (Driediger and Bhatiasevi, 2019). Analysis of online reviews is necessary to segment the consumers based on their satisfaction level of the consumers. A supervised machine learning model is needed to classify the consumers based on their positive and negative reviews.

This study is classified into five sections. Section 1 consists of the introductory part of the research. Section 2 focuses on the theoretical background of the study. Section 3 consists of research methodology, Section 4 and Section 5 contain the result and conclusions of the research.

2 Theoretical underpinning

Several kinds of research have been conducted to determine the buying behaviour of consumers towards online grocery stores. Rarely, such types of the study found during COVID-19, especially research-based on online reviews of consumers towards online grocery stores are still missing. Taking this into consideration, the literature reviews of this study are classified into the following sections:

1 role of online grocery stores during COVID-19

2 online consumers' reviews

3 sentiment analysis for online reviews

4 naïve Bayes classification to segment the online reviews.

2.1 Role of online grocery stores during COVID-19

During COVID-19, the availability of products in online grocery stores is one of the most important factors. Consumers started panic-buying for the upcoming months due to uncertainties. Most of the online grocery stores were facing the problem of a shortage of products during the pandemic. The business of online grocery stores increases tremendously during COVID-19 (Naeem, 2021). The impact of COVID-19 on European countries was worse than India. The transport volume was influenced by COVID-19. Due to government restrictions, the supply chain system of grocery items was badly affected and disrupted. In online grocery shopping, the supply chain plays a crucial role. This has changed consumer buying behaviour intentions (Loske, 2020). Such study is missing in the Indian context. Disruption of food supply was the major reason that consumers move towards online grocery stores. Most of the online grocery stores put barriers to unlimited purchasing for an individual consumer. They restricted the consumers to limited purchases due to disruptive supply chain management (Workie et al., 2020). COVID-19 has changed the external environment of businesses (Alam et al., 2021). Online grocery stores are also untouched by it.

The responses of the consumers have also changed drastically. Consumers started giving their responses through an online platform. Pandemic has a significant impact on consumers' purchasing patterns. The mobility of the common people was restricted during the pandemic, so consumers moved towards an online platform to fulfil their needs and requirement (Hall et al., 2020). The social media platform has increased the engagement of the consumers and influenced the purchasing behaviour of consumers. Different online platforms have made people panic and forced them to panic about buying. The online sellers were also closely monitoring consumer behaviour and tried to increase their sales as much as possible (Naeem, 2020). It will be interesting to find out the changes that occurred in consumers' behaviour towards online grocery stores.

2.2 Online consumer's reviews

In today's digitalised world, online reviews have become very crucial for companies. Online reviews have a significant impact on the consumer's purchasing decision. It is one of the most powerful tools to influence the bulk customers. Both negative and positive reviews matter for the companies. Online word of mouth has a significant impact on sales volume (Hu et al., 2008). Before purchasing the products through online mode, most of the consumers read and evaluate the online reviews. These reviews are relevant information for the consumers. These reviews have an impact on the cognitive thinking of the consumers. The role of emotions in online word of the mouth needs to analyse and evaluate because it plays a crucial role in the consumer decision-making process (Ruiz-Mafe et al., 2018). Online feedback system engages the consumers to write online reviews, it also helps the companies to know the sentiment of the consumers. It also helps to understand the satisfaction level of the consumers. Negative reviews are more important for companies. It helps them to do the modification in their existing products as per the reviews. Reading the mind of the consumers is a complex task, so the analysis of online reviews is a better way to predict the sentiment of the consumers (Thakur, 2018).

2.3 Sentiment analysis for online reviews

Sentiment analysis is one most powerful tool for text mining. Sentiment analysis is used to convert text data into valuable information. Sentiment analysis assists the marketers to know the sentiment or emotions of the consumers. It can be used for both supervised and unsupervised machine learning models. Three important techniques used for sentiment analysis are bag-of-words, Word2Vec and TF-IDF (Drus and Khalid, 2019). Retailers can use sentiment analysis to develop an effective marketing strategy. It enables retailers to obtain direct consumer feedback and improve their products and services to meet their needs (Ibrahim and Wang, 2019a). Sentiment analysis is used to evaluate the sentiment of the consumers. Due to the rapid development of e-commerce, it is become indispensable for the consumers as well as for the companies to extract online reviews. It is impossible to analyse these massive data manually. Sentiment analysis is one of the best techniques to analyse these data. It explained both positive and negative polarity and extract meaningful opinions from online reviews (Tang et al., 2019). An effective machine learning system supported by data mining of online reviews could be able to predict the behaviour of the consumers at the digital platform. Online reviews show the influencer power and represent the emotional polarity of the consumers (Li and Wu, 2010). Online marketing is triggered by artificial intelligence-based software. It is changing traditional marketing into digital marketing that's artificial (Capatina et al., 2020). Consumers usually get influence by the quality of information available on the digital platform. Previous data and reviews of the consumers are helping to develop the predictive model. Machine learning models can be developed using sentiment analysis which is a very powerful forecasting tool (Ravi and Ravi, 2015). Predicting the behaviour of consumers is essential for the survival of an organisation, so it is requisite to know the feedback of the consumers. Consumers express their reviews about the products and services on online platforms. The writing style of the consumers also varies, such differential writing styles reflect the heterogeneity of the consumers. Sentiment analysis helps to overcome this problem (Hu, 2012).

2.4 Naïve Bayes classification to segment the online reviews

Naïve Bayes classification can be used to classify the consumers and predict their buying behaviour. It could be used to develop the artificial intelligence model which can predict the future purchase intention of the consumers. The application of Naïve Bayes classification in marketing is very broad. It is a probabilistic model based on conditional probability (Baesens et al., 2004). Bahari and Elayidom (2015) have developed the CRM data mining framework using a naïve Bayes classification. Naïve Bayes is a probabilistic classifier technique based on Bayes theorem. It gives more accurate results than the random decision tree classifier and k-nearest neighbour (Ghazzawi and Alharbi, 2019). This model can help to retain the existing consumers and maintain a healthy relationship between customers and the organisation. Naïve Bayes is a strong classification tool for the machine learning models (Wu et al., 2015). Sentiment analysis supported by the algorithm of the naïve Bayes classifier can generate a more accurate prediction model (Sundararaj and Rejeesh, 2021). It is a more sophisticated classifier than others. The naïve Bayes classifier model helps the credit risk manager to do the segmentation of the consumers. Due to the high accuracy rate, this classification is used in the banking sector (Krichene, 2017). Jin et al. (2016) developed a model based on a naïve Bayes sentiment classifier to predict the sentiment polarities of the consumers. They have tested support vector machine and logistic regression also but found naïve Bayes classifier is the best estimator. Naïve Bayes classifier is best suitable for analysing the content available on the social media platform (Ray et al., 2020).

It is a probabilistic technique used for classification. Naïve Bayes is based on conditional probability.

$$Conditional\ Probability = \frac{P(A.C)}{P(A)}$$

If we consider the label class and attribute as a random variables.

The given record of the attribute is (A_1, A_2, A_3, …………, A_n).

The objective is to predict the value of C.

If we are looking to determine the value of C that maximises the value of $P(C| A_1, A_2, \ldots, A_n)$.

$$Posterior = \frac{Prior \times Likelihood}{Evidence}$$

The posterior probability of $P(C| A_1, A_2, \ldots, A_n)$ for all values of C is calculated by:

$$P\left(C\middle|A_1, A_2, A_3, \ldots, A_n\right) = \frac{P\left(CA_1, A_2, A_3, \ldots, A_n\right).P(C)}{P\left(A_1, A_2, A_3, \ldots A_n\right)}$$

Select the value of C which maximises

$$P\left(A_n\middle|B_1, B_2, B_3, \ldots, B_m\right)$$

which can also be expanded in the chain rule

$$\begin{aligned} P\left(A_n\middle|B_1, B_2, B_3, \ldots, B_m\right) &= P\left(B_1, B_2, B_3, \ldots, B_m, A_n\right) \\ &= P\left(B_1\middle|B_2, B_3, \ldots, B_m, A_n\right)P\left(B_2\middle|B_3, B_4, \ldots, B_m, A_n\right) \\ &\quad P\left(B_3\middle|B_4, B_5, \ldots, B_m, A_n\right) \\ &= P\left(B_1\middle|B_2, B_3, \ldots, B_m, A_n\right)P\left(B_2\middle|B_3, B_4, \ldots, B_m, A_n\right)\ldots \\ &\quad P\left(B_{n-1}\middle|B_m, A_n\right)P\left(B_n / A_n\right)P(An) \end{aligned}$$

Now, assumes that all the values of B are mutually exclusive.

$$P\left(B_n\middle|B_{i+1}, \ldots\ldots\ldots, B_n, A_n\right)P\left(B_i / A_n\right)$$

The model is expressed as follows:

$$\begin{aligned} P\left(A_n\middle|B_1, \ldots\ldots, B_n\right) &\alpha P\left(A_n, B_1, \ldots\ldots, B_n\right) \\ &\alpha P\left(A_n\right)P\left(B_1\middle|A_n\right)P\left(B_2\middle|A_n\right)P\left(B_3\middle|A_n\right)\ldots\ldots \\ &\alpha P\left(A_n\right)\prod_{i=1}^{n} P\left(B_i\middle|A_n\right) \end{aligned}$$

where α = proportionality.

3 Methods

3.1 Data collection

We analyse the data collected from the e-commerce platform. The study is based on text data collected from BigBasket, Grofers, Spencers and Amazon. These four companies are the biggest Indian online grocery seller in the virtual world. The reviews of the respondents towards these four online grocery stores have been collected from different online sources which are mention in Table 1. The noisy data having inconsistency features are removed from the data. A total of 1000 data has been collected for the research. The period of data collection was January 2020–December 2020. We used the Jupyter notebook for data analysis. Jupyter notebook is a python-based data scientist open-access software available on the Anaconda platform (Martini et al., 2020). We avoided the bias reviews and try to keep the variable of language consistent. The reviews have been classified from 1-star to 5-star. In this study, we have considered only 1-star (extreme negative) and 5-star ratings (extremely positive).

Table 1 Reviews of online grocery stores

Online grocery stores	*No. of reviews*	*Source*
Big Basket	120	Reviews of Bigbasket.com (Sitejabber, 2020)
Grofers	430	GROFERS.COM reviews, feedback, complaint, experience, customer care number (MouthShut.com, 2020)
Amazon	315	Grocery: Amazon.in: clothing and accessories
Spencers	135	Reviews of Spencersonline.com (Sitejabber, 2020)

3.2 Data analysis

The data has been converted into CSV file (comma separated file). Jupyter notebook is installed from the anaconda platform. Jupyter is a python-based data scientist software. Scikit-learn library is installed in jupyter notebook. Scikit learn is one of the most important machines learning libraries in python (Kramer, 2016). Numpy and panda library is installed which is used for working with arrays and cleaning the data (Palkar et al., 2017). The data was mixed and in unstructured form. First of all, we have done the data pre-processing to clean the data. We convert the text data into a meaningful piece of data by applying the tokenisation process. Tokenisation is the process of converting the data into a random string of characters called a token (Gheorghe and Liao, 2012). After that, stemming has done to catalogue the related words followed by lemmatisation to apply the morphological analysis of words. Stemming is the process of lessening the word into its stem (Conway and Connor, 2016). We do the stemming and lemmatisation and then apply to stop words. Lemmatisation is the process of assembling similar words into a single word and using vocabulary and morphological analysis of words adequately (Rojas-Rivas et al., 2019). Then, we remove the stop words from the text data. Stop words are the common words that are not required in data analysis (Agerri et al., 2015). In the dataset, we have three arrays. The first array contains the reviews of the consumers towards online grocery stores in form of text messages, the second one consists of star ratings (1-star or 5-star) and the last third array consists label of the ratings. 1-star label as neg and 5-star as pos. The CSV data file was imported into Jupyter notebook by using the pd.read_csv command. TF-IDF is used to determine the importance of words in the corpus (Kauffmann et al., 2020). Term frequency and inverse document frequency (TF-TDF) is used to determine the relevancy of the online reviews of consumers. TF-IDF technique quantifies the words of the reviews to draw the meaningful context from the text mining (Zhang et al., 2011). It is used to convert the words into vectors. TF-IDF is calculated by multiplying the TF value with the IDF value. The value of TF-IDF increases proportionally to the number of times a word appears in the document and is offset by the number of Frequency in the corpus that contains the word (Tobarra et al., 2014).

$$TF(Term\ frequency) = \frac{No.\ of\ repetition\ of\ words\ in\ sentence}{No.\ of\ words\ in\ sentence}$$

$$IDF(Inverse\ document\ frequency) = \log[(No.\ of\ sentences)/(No.\ of\ sentence\ containing\ words)]$$

$$Measure\ of\ the\ relevancy\ of\ a\ word\ to\ a\ document = TF \times IDF.$$

4 Result

4.1 TF-IDF calculation of text data

The text is converted into a CSV file and imported into Jupiter notebook. The first four reviews are shown in the screenshot.

Sorting of words has been done to identify the top 15 important words based on their TF-IDF value. The words with their TF-IDF value are shown in Figure 1.

Figure 1 Words with their TF-IDF values (see online version for colours)

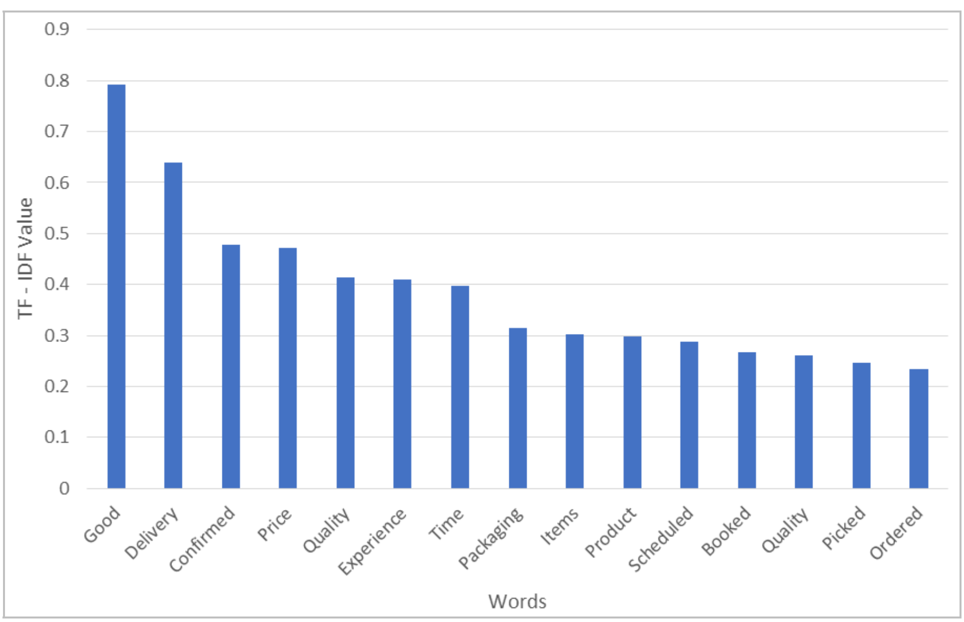


Table 2 Sample of the text data

	Messages	*Sentiment*	*Label*
0	It is best app for ordering groceries	0	Neg.
1	Delivery time is perfect	1	Pos.
2	Customer service is excellent	1	Pos.
3	Customer service is also really good as once I…	0	Neg.
4	The products are not at all costly and are che…	1	Pos.

In Figure 1, the values of TF-IDF show the relevancy of the words in the text data. The top fifteen important words are good, delivery, confirmed, price, quality, experience, time, packaging, items, product, scheduled, booked, quality, picked and ordered having their TF-IDF values 0.793, 0.639, 0.478, 0.471, 0.413, 0.409, 0.398, 0.315, 0.303, 0.297, 0.287, 0.266, 0.260, 0.247 and 0.234.

4.2 Classification model

Naïve classification is used to do the classified the text data based on 1-star and 5-star ratings. The shape of the data is (1,000, 3) means three columns and 1,000 rows. The rows represent the reviews and the columns show messages, sentiment and labels. Before running a naïve Bayes classification, the data is divided into training and test set. The data is divided into a 70:30 ratio. 70% (700) data was taken for the training set and 30% (300) data was taken for the test set. A confusion matrix is determined by importing confusion_martix from the sclearn.matrix. Multinomial naïve Bayes classification is used which is best for text classification. MultinomialNB is imported from sklearn.naive_bayes. The recall value of the training and test data has been calculated. The recall value of training and test sets are 0.939 and 0.762. Recall value shows the ratio of correct positive prediction over all positive predictions. The calculated value of the training and test set proved that model is good and able to measure the sensitivity. Further, the precision value of training and test sets is determined which is 0.912 and 0.767. The precision value represents the positive predicted value. The obtained precision values of training and test set show that the model is good. The f1 score of training and test sets are 0.925 and 0.764 respectively. The f1 score shows the accuracy of the model and the balance between recall and precision values. Precision-recall curve has been plotted which shows the relationship between sensitivity and positive predicted value. Thereafter, receiver operating characteristic has drawn to shows the relationship between sensitivity and specificity.

Precision and recall are used to evaluate the exactness of the classier model. Precision is the percentage of a result that is relevant. The percentage of relevant results that the machine learning model recalls is referred to as recall (Li and Li, 2013). Figures 2 and 3 shows the trade-off between the precision and recall value of training and test set. Average precision (AP) value shows the relevancy of the model. A good precision-recall has a greater AUC (area under curve) value. It shows the performance of the classification model. The AP value is 0.99 which shows that the training set is perfect for the model development. In the test set, the AP value is 0.86 which proved that the supervised machine learning model is good and can be used for classification. The model's AP values for training and test sets are 0.99 and 0.86, respectively, indicating that it can accurately classify all relevant results.

Figure 2 Precision-recall curve of the training set (see online version for colours)

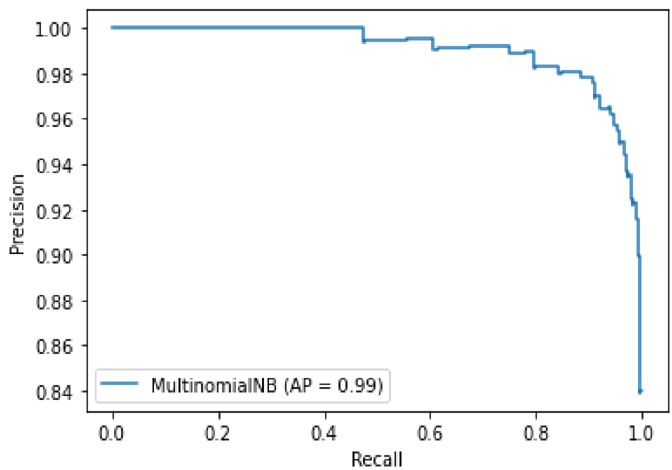


Figure 3 Precision-recall curve of the test set (see online version for colours)

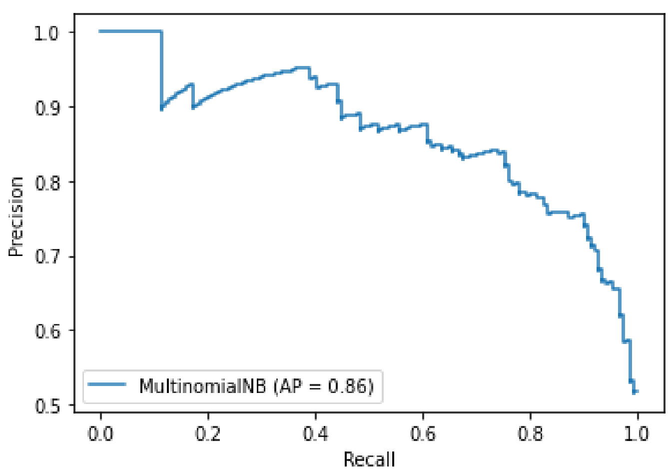


Table 3 Confusion matrix of training set

		Actual	
		5-star	*1-star*
Predicted	5-star	356	34
	1-star	23	287

Table 4 Confusion matrix of test set

		Actual	
		5-star	*1-star*
Predicted	5-star	119	36
	1-star	37	108

The ROC curve is used to forecast a binary result. The receiver operating curve (ROC) shows the graph between false positive rate and true positive rate (Chung, 2014). Figures 4 and 5 represent the ROC curve of training and test set. The ROC shows the trade-off between true positive value and false-positive value. The area under the curve (AUC) values of the training and test set are 0.99 and 0.87, which proved that the classification model is good.

Figure 4 ROC curve of the training set (see online version for colours)

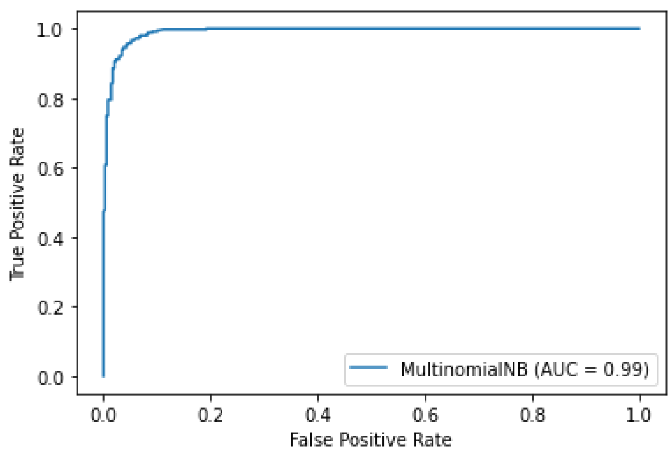


Figure 5 ROC curve of the test set (see online version for colours)

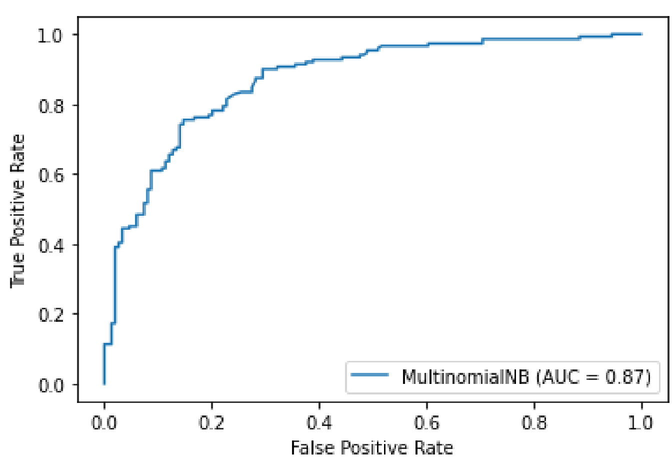
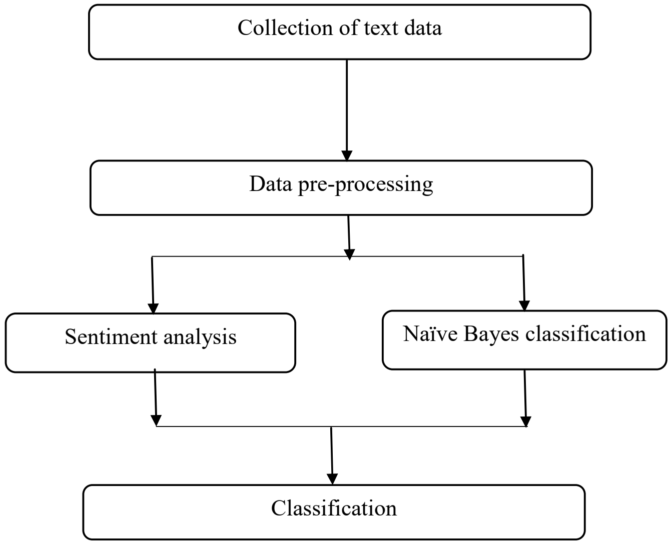


Figure 6 Supervised machine learning model



5 Discussion

5.1 Research implications

This study aims to understand the deep learning of the reviews of the consumers towards online grocery stores. To achieve the objective of the research, we explored sentiment analysis by applying TF-IDF followed by naïve Bayes classification. Analysing online reviews is the cheap and best way to get the feedback of the consumers. A rare study has been done on text mining to analyse the reviews and ratings given by the consumers on the online platform. During COVID-19, the role of online grocery stores was very crucial. People have started panic buying due to COVID-19. So, it is become very difficult for online grocery stores to delivered products on time and managed consumer's satisfaction (Hall et al., 2020). Kauffmann et al. (2020) used sentiment analysis to create a modular framework that assists the marketing manager in making decisions. The established framework provides additional information based on online reviews, which is crucial for marketers to determine consumers' buying habits. This research looks into the possibilities of developing a machine learning model for online grocery stores based on customer feedback. This study focussed on analysing the online feedback of the consumers during COVID-19. Sentiment analysis is used to develop a supervised learning model. The model developed is a classification model based on 1-star and 5-star ratings. TF-IDF value is used to do the sentiment analysis. Sentiment analysis reviews and evaluates the sentiment of the consumers (Mäntylä et al., 2018). The sentiment analysis tool can effectively anticipate the sentiment of customer reviews. The results of sentiment analysis shed light on the relevance of consumer online reviews on digital platforms (Al-Natour and Turetken, 2020). Sentiment analysis could be used to develop the machine learning model which can forecast the future demand. The integrated system based on online reviews can anticipate results with more accuracy (Capatina et al., 2020).

Consumer reviews on various digital platforms are extremely important for businesses. Sentiment analysis is used to turn these reviews into useful information (Ibrahim and Wang, 2019b). The TF-IDF values show the relevancy of the words in the reviews. TF-IDF is better language modelling than a bag-of-words and Word2Vec (Abirami et al., 2017). During COVID-19, online grocery stores faced a lot of hurdles while supplying products to the consumers, so unstructured online reviews help them to know the sentiment of the consumers. This analysis helps the online grocery stores to improve their services. This study developed the classification model based on positive and negative reviews of the consumers. 1-star shows the negative sentiment of the consumers whereas 5-star shows the positive sentiment. Naïve Bayes classification is used to develop the classification model. Naïve Bayes do more accurate classification in comparison to other classification tools (Muralidharan and Sugumaran, 2012; Elangovan et al., 2010; Soria et al., 2011). TF-IDF and naïve Bayes classification give more effective and efficient results by doing sentiment analysis of reviews of online grocery consumers.

5.2 Managerial implications

The outcome of this study helps online grocery stores to improve their services and identify the keywords of online reviews based on which consumers give positive or negative reviews. The online grocery stores enhance the level of their services by using the classification model developed in this study. This study is based on online reviews of the consumers which are unstructured and complex. Marketers may use this model while segmenting the consumers based on their satisfaction level of the consumers. Marketers must analyse the online reviews of the consumers because it reflects the actual feedback of the consumers. Marketers may use these reviews to retain the consumers and create loyalty among them. TF-IDF has identified the important keywords which reflect the important attributes having an impact on the online grocery stores to attract consumers. In the top fifteen identified words, some are delivery, price, quality packaging, time, scheduled, quality, etc. which helps the online grocery stores to improve their quality. In India, online purchasing is at the growth stage. Online grocery stores are also trying to take the advantage of it. Presently, the Indian Government is focussing on digitalisation. So, Indian consumers are moving towards the digital platform to purchase the products. Online grocery stores are also untouched by it. Positive reviews of consumers attract new customers towards online grocery stores. Negative reviews help marketers to understand the cause of negative sentiment and improve their services. In this study, we developed a classification model which is applied to online grocery stores. The findings of the study demonstrated that machine learning techniques are not just useful for technical experts; they also assist marketers in developing effective and appealing marketing plans based on actual consumer feedback. This study assists marketers in understanding consumer satisfaction in terms of star ratings.

6 Conclusions

The objective of this research was to create a supervised learning model for online grocery retailers. Consumer reviews were used as a source of information for the study. The research was carried out in India during the period of COVID-19 when the country was under lockdown. The relevancy of the words in the reviews was determined using TF-IDF. According to their TF-IDF value, the unique words are listed in descending order. In-text data, a higher TF-IDF indicates greater relevancy. Additionally, the supervised machine learning model is built using the naïve Bayes classification. The best classification tool for dealing with large online reviews is naïve Bayes. The classification model was created using 5-star (very good) and 1-star (extremely negative) ratings. This model could be used to more correctly forecast customer purchasing patterns in the shortest amount of time. Consumer behaviour varies dramatically during pandemic COVID-19. This classification model's output assists online grocery stores in improving their offerings. Further research may be done to see whether customers are getting the services they anticipate from online grocery retailers. For marketers, online reviews are critical. Marketers can use online reviews to acquire real feedback on the services of online grocery stores. Customers' decision-making is significantly influenced by online reviews. This model might be used to segment customers depending on their purchasing habits, which could be the study's next focus. This study turns online reviews into meaningful data using data scientist tools. The naïve Bayes theorem was used to construct a framework based on sentiment analysis for online grocery retailers in this study.

There are some limitations to this study. Only 1 and 5-star ratings were used in this study, which was based on consumer reviews posted online. This study did not take into account internet reviews with a rating of 2, 3, or 4 stars. Another limitation is that this study is based on online reviews of four different online food retailers. The study's future scope will include exploring the possibilities of the naïve Bayes theorem and deep learning technologies for online grocery businesses.

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