Cite this research:
Patel, N., Trivedi, S. (2020). Leveraging Predictive Modeling, Machine Learning Personalization And NLP Customer Support and Chatbots to Increase Customer Loyalty. EQM ResearchBerg, 3(3), 1–24.

check for updates

Article history:
Received:
March/10/2020
Accepted:
April/30/2020

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Leveraging Predictive Modeling, Machine Learning Personalization, NLP Customer Support, and AI Chatbots to Increase Customer Loyalty

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Abstract

AI, ML, and NLP are profoundly altering the way organizations work. With the increasing influx of data and the development of AI systems to understand it in order to solve business challenges, the excitement surrounding AI has grown. Massive datasets, computer capacity, improved algorithms, accessible algorithm libraries, and frameworks have compelled today's organizations to use AI to enhance their operations and profits. These technologies aid every kind of industry, from agriculture to finance. More specifically, AI and ML, and NLP are assisting organizations in areas such as customer service, predictive modeling, customer personalization, picture identification, sentiment analysis, offline and online document processing. The purpose of this study was twofold. We first review the several applications of AI in business and then empirically test whether these applications increase customer loyalty using the datasets of 910 firms around the world. The datasets include the integration scores of four different AI features, namely, AI-powered customer service, predictive modeling, ML-powered personalization, and natural language processing integration. The target is the customer loyalty measure as binary. All the features are measured on a 5-pint Likert scale. We applied six different supervised machine learning algorithms, namely, Logistic regression, KNN, SVM, Decision Tree, Random Forest, and Ada boost Classifiers. the performance of each algorithm was evaluated using confusion matrices and ROC curves. The Ada boost and logistic classifiers performed better with test accuracies of 0.639 and 0.631, respectively. The decision tree and KNN had the performance with accuracies of 0.532 and 0.570, respectively. The findings of this study highlight that by incorporating AI, ML, and NLP, businesses may analyze data to uncover what's useful, gaining valuable insights that can be used to automate processes and drive business strategies. As a result, firms that wish to remain competitive and increase customer loyalty should adopt them.

Keywords: AI, Business, Customer loyalty, Machine learning, NLP, Predictive modeling

Introduction

Businesses can now gather massive amounts of data and utilize it to get useful insights on how to enhance the entire customer experience. information is still generally and readily accessible for use in product and service enhancements, ranging from click and revenue generation to sale and payment histories to online comments and discussions (Sagiroglu & Sinanc, 2013). The same is true for customer service, where data may be gathered across numerous touchpoints for critical contact center metrics such as average handling time, initial contact resolution, customer attrition, contact medium, or comments on social media to determine how happy clients are with the service (Vossen, 2014).

With the growth of Big Data, Advanced Analytics (ML), and Predictive Modeling, getting insights is quickly becoming the norm for optimizing operations and consumer experiences (Strickland, 2014). It is applicable to every sector as firms depend on recurring transactions. Investing in a positive customer experience is a solid growth strategy that leads to increased sales. Social media offered a platform for businesses to directly communicate with consumers. Chatbots build on this by allowing businesses to deliver a service without the need of real people. These bots reply to inquiries or orders designed to mimic real-world conversations.

Bots are currently used by businesses to communicate with consumers in the most effective way possible (van Eeuwen, 2017). They are successful in gathering and disseminating information to several users at the same time. They may also serve as a replacement for emails by sending alerts and updates. Bots may also connect to other applications and collect information from them. As a result, they can provide a more customized content.

A recommender system is a data processing system that uploads data suited to a user's interests, choices, or activity history on a particular product (Tsai, 2016). Based on their profile, it may anticipate a given user's desire for a product. Customers may simply and swiftly locate the things they are searching for by using product suggestion systems (Shani & Gunawardana, 2011). So far, several recommender systems have been built to locate things that the user has previously viewed, purchased, or engaged with. The recommender system is an excellent marketing tool, particularly for e-commerce, and it may also help to increase profits, sales, and profits in general (Duan et al., 2019).

Sentiment analysis is a popular NLP approach being used in many businesses. It is the act of comprehending an opinion on a specific issue via written or spoken language, and correct forecasts are seen to be a game changer in obtaining financial sector performance (Salinca, 2015; Sanguansat, 2016). Organizations employ experts, industry experts, and trade analysts to watch and analyze the influence of different events on the markets (Rokade & Aruna, 2019). Their task may be made easier by combining NLP alongside ML and AI approaches, which are useful for analyzing data from the web, news, blogs, and social media sites. They can forecast market swings, allowing businesses to make sound judgments at the proper moment. When utilizing sentiment analysis, for example, terms like 'excellent,' 'revenue,' 'advantage,' 'good,' and 'improvement' may be assigned a positive value, but words like 'risk,' 'drop,' 'insolvency,' and 'loss' are assigned a negative value. Making sense of the text found by NLP and ML enables for reliable predictions (Drus & Khalid, 2019).

Likewise, NLP's implementation in company or organization can be seen in the following ways: sorting emails and recognizing spam (by analyzing text); improving safety through voice identification; retrieving data from huge sets of data; employing web chatbots for offering exceptional customer assist; supporting business insights; placing personalized advertising online using keyword algorithms; and analyzing rivals and the industry using NLP. NLP may be used in E-Commerce systems to analyze customer behavior based on comments, postings, reviews, ratings, and so on (text analysis) (Shafin et al., 2020). It may also offer excellent customer assistance through virtual assistants, who can react to consumer enquiries in a variety of media, such as text, voice, or video clip (Zoghbi et al., 2016).

The impacts of predictive modelling, machine learning personalization, AI chatbots, and NLP on customer loyalty

1. Predictive modelling

Prescriptive modeling is the use of large data, mathematics, and modeling approaches to create future predictions. It examines both current and historical data to identify trends in order to predict the possibility of that very same behavior occurring once more in the future. Prescriptive modeling is a proactive strategy as opposed to a reactive one. Knowing what potential consumers want or purchase next may provide businesses with a major competitive edge. Predictive analytics may help businesses improve personalization, promote new business and loyalty, and improve client satisfaction (Burez & Van den Poel, 2009; Hadden et al., 2007).

This creates an opportunity for companies since more involvement via digital platforms implies more data gathered. And that data may be used to boost consumer happiness and loyalty. Prescriptive modeling may assist businesses in achieving the sweet spot of customer service: anticipating what the consumers want. And it considerably improves the capacity to provide them with an improved degree of customer experience. Predictive analytics allows businesses to target and keep clients by predicting the likelihood of future events using facts, statistical models, machine learning, and deep - learning techniques

(Eckerson, 2007). It gives businesses the ability to turn existing information into new insights.

It also works by combining current and historical consumer data with what customers are saying on social networks as well as other public channels. As a result, sellers may personalize offerings in novel ways and provide improved Customer experience across a variety of channels. Predictive analytics enables businesses to develop tailored content, data, goods, and services that customers anticipate even before they realize they want them (Bradlow et al., 2017).

Recognizing consumer requirements

With the growth of social networking, it is now simpler than ever to reach consumers. As a result, rather than depending on basic assumptions, it is critical to undertake research and apply analytics to give the best program feasible. Apps like Instagram and Facebook feature direct messaging options that enable businesses to hear both positive and negative feedback from their clients. Businesses who use the correct social media channels for their organization may be extremely helpful in determining client needs. Not all consumers are similar, and not all incentives will result in client loyalty. Knowing what a consumer need is critical when developing a loyalty program. Understanding their demands will allow companies to tailor the program to their demands and assure its effectiveness.

Client Loyalty Evaluation

The higher the retention rate, the more consumers redeem their incentives, and hence the greater the proportion of loyal customers (Wassouf et al., 2020). Assessing engagement ratio or involvement level is similar in that it shows the proportion of consumers who are actively participating in the loyalty program (Wassouf et al., 2020). This will assist business in determining if its present brand loyalty items are successful offers or not.

Prescriptive modeling may assist organizations fine-tune the overall architecture of customer loyalty and measure how much money their consumers pay and how essential they are to the business. As a result, firms may better understand their customers' loyalty, allowing them to make improvements to their loyalty programs and garner greater loyalty. Loyal customers are basically brand ambassadors; therefore, loyalty programs should emphasize as much customer connection as possible.

Client retention rate calculation

Because there are so many different reasons why a client can quit a business, it is critical to calculate the customer loyalty and retention and devise strategies to keep consumers from leaving (Zaki et al., 2016). Companies may also monitor business customer loyalty level, website clickthrough rate, and client satisfaction feedback outcomes to determine success rates. A greater percentage of customer retention is likely to result in a higher level of participation in a rewards program. As a consequence, more consumers will be loyal to the company, and the client loyalty program awards will form strong links, enabling relationships to form between those loyal consumers and the firm, resulting in lasting loyalty.

2. Chatbots loyalty

Customers appreciate speedier service provided by chatbots, but a human touch may be the perfect addition. Bots have shown to be effective agents for answering simple inquiries. They are configured with basic principles and AI logic to replicate human written speech.

As customer requirements and preferences shift and restructure the corporate structure, practically all clients want client service agents to be available 24 hours a day, seven days a week. If administered by a human operator, this is almost impossible. Chatbots are succeeding in this circumstance by offering the appropriate assistance and service (Cheng & Jiang, 2020). A human-AI hybrid may transform the customer service, with people totally focused on harnessing AI's speed, efficiency, and reach, and the chatbot trained to provide 100% customer pleasure by addressing their concerns on time.

Technology has aided the chatbot in comprehending the nature of each discussion and addressing each customer's questions. One should recognize that as humans, people always want to communicate to a real person; nevertheless, the only constraint would be that a real human cannot constantly be available online. This void is filled by a chatbot with a human element (J. Trivedi, 2019).

Gather data and learn about business's consumers.

Chatbots may help businesses collect information and develop a better understanding of clients. This is one of the chatbots' most powerful abilities. The manner a company chooses to develop their chatbot will affect how well it works. As a result, a companies are developing the chatbots to be ready to gather crucial information about their consumers (Rossmann et al., 2020). It will accomplish this by researching and recording their shopping habits. It will also serve as a management database, storing basic consumer information.

The bot insight will be especially valuable if company is a merchant of food or apparel (or fashion in general). Knowing the patterns of clients can offer a decent notion of the things they like. Firms may utilize this information to properly manage their inventories. Chatbots may also keep information about the kind of inquiries they get. This provides company managers with a notion of the kind of queries that clients are likely to ask. It even helps to prepare the company to respond or deal with similar problems in the future.

Answering customer questions

This has been the most basic use of chatbots for small enterprises. A firm would not perform well if it does not include that as one of ways to leverage the chatbot for client acquisition. Bots serve as the initial point of interaction between consumers and businesses. This is especially important if business operate in a sector with a lot of terminology; there is a good probability that people may contact customer services with simple queries (Rese et al., 2020).

As a result, companies may feed the chatbot with the top commonly requested queries. This will save both the consumer and the company a lot of time. It will even boost client satisfaction since they will get responses quickly. Chatbots may be more valuable to foreign enterprises for this reason. Chatbots provide 24-hour customer care and can serve consumers from all around the globe, regardless of time zone (Sheehan et al., 2020).

Customize the content experience

Many organizations now utilize chatbots simply for content delivery. It is now an element of their strategy. These bots give clients with material that is tailored to their unique requirements. Content that has been particularly selected for them (Nordheim et al., 2019). This manner, the company may increase its social media engagement without seeming to spam or compel customers (Følstad & Skjuve, 2019).

Multilingualism and chatbot.

There are several languages in the globe, and everyone, quite plainly, likes to speak their native language. As a result a company may make better usage chatbot by developing them to carry on a conversation (Abbet et al., 2018). One would not expect all of business clients to share a common language if they were dispersed all across world. As a result, companies can plan for the clients to be able to connect to the business in their home dialect or first language. This allows the consumers to connect with business more easily. They will be much more inclined to contact the customer service department. This simplicity of interaction boosts your capacity to keep consumers.

The company's client retention will improve with multilingual chatbots. As a result, business should ensure that language does not hinder the progress company want to achieve.

Make shopping simpler.

Companies can make it feasible for the clients to buy right from the live chat in order to keep them with the chatbot. Businesses can continually explore for methods to enhance the chatbots and give your consumers additional options.

By introducing additional features to the chatbots, you would be able to maintain clients. You may also instruct the bots to direct clients back to the online store. To make payments simpler, your chatbot may be able to function as a payment instrument. When financial transactions are simple, the consumers will be more likely to return and buy more. As a result, firms can also utilize a chatbot to keep them or get new ones.

3. ML personalization

In recent years, there has been a tremendous growth in the usage of digital technology to provide individualized experiences (Piccoli et al., 2017). It is now feasible to provide unique material suited to each customer's interests and demands, making suggestions simple and straightforward. A component of machine learning is the creation of algorithms that can provide content and relevance recommendations to clients, much as human speech / language specialists do with actual people. Machines, unlike real speech / language specialists, lack emotions, stereotyping, and biases (Berry et al., 2013).

Machine learning entails developing recommendation engines that can access a broad range of data resources, including private data from clients, external corporate data, and websites. Recommendation engines enable businesses to create a relevant, tailored experience for every consumer, regardless of their previous purchase patterns or preferences (Bleier et al., 2018). Retail giants are increasingly using recommendation systems to offer tailored shopping experiences for specific consumers. Customers generally welcome these suggestions, but they are particularly successful with millennial consumers, who are more inclined to buy things they see promoted on media or in magazines. Machine learning is being used by the organizations involved to create a recommender system that combines the most of all previously acquired external data, integrates it with analytical and NLP techniques, and improves the resultant suggestions (Vesanen & Raulas, 2006).

Machine learning enables not just the suggestion of tailored experiences and information, but also the advice of products based only on historical purchasing history. Machine learning predicts what consumer will purchase in the next by using historical purchasing behavior, allowing recommendation engines to propose various things based on past orders and how other consumers have reacted to these products previously (Verhagen et al., 2014). Machine learning system suggestions are often more focused than human suggestions, however that is not always the case. Suggestions from a machine learning model may still be very personalized, especially if they are produced for a specific individual by someone they know.

Friends and family recommendations are also quite useful. In other circumstances, individuals just like giving recommendations to one another and feel compelled to offer their opinions on certain things. This advice, however, may be misleading and may not take into consideration Machine learning may be used to make suggestions for any product based on individual data obtained from a variety of sources.

Machine learning or a.i. program recommendations are much more useful than a human suggestion. Friends and family recommendations are impacted by their own perception of the product as well as their own personal conduct toward the product in issue . Recommendations from shops and manufacturers are impacted by their own requirements to market their goods, but recommendations from friends / relatives are more personal and naturally more customized to a particular set of individuals (Walter et al., 2008).

When recommendations are focused, they are much more powerful. Recommendations aimed towards those who have similar buying habits will result in more purchases since the system can tailor its suggestions to those people. Because the suggestions may be indiscriminate, recommendations which are more broad and applicable to the purchasing community will result in fewer purchases (Lu et al., 2012). Overly broad suggestions might lead to biased and erroneous recommendations. Overly precise suggestions will lead to suggestions for just one sort of product.

Machine learning may also be used to produce customised suggestions across many shopping channels or stores. Recommendations are an incredibly effective technique for increasing sales and retaining consumers. In the instance of an online retail site, tailored suggestions may greatly increase sales and make comparison shopping easier for consumers. This allows retailers to offer more things to their clients and enable them to make purchase choices based on what customers truly want now rather than what others propose. Machine learning may help audiences produce more tailored suggestions. The strength of a suggestion is determined by who makes it.

There are several strategies to maximize the value of customised suggestions. The most appropriate advice is always one that is suited to the audience. When someone searches for a subject that is relevant to their requirements, suggestions for those keywords will appear, bringing the customer even sufficiently close to the item or prospect being presented.

Machine learning also makes it simple to modify suggestions. All a company needs to do is offer the visitor with what they requested and inform the computer what type of suggestion they should make. It makes no difference what sort of advice they requested since the system will recognize it and then request a personalized recommendation.

When businesses provide customized suggestions, the visitor understands that the advice are suited to them specifically. They also know they are receiving those who have done their research and knows the importance of such advice. This fosters trust and is an important step toward achievement. They produce more sales leads, turn those prospects into paying customers, and develop their reputation by promoting their services and goods to others.

When a consumer receives individualized advice, he or she is more inclined to buy than if they received a generic recommendation. Companies understand the importance of providing customized advice. Companies must exercise caution when customizing advice. They must choose suggestions that will assist the company in achieving its objectives. If the corporate objectives are overly broad, the suggestions may do more damage than benefit. Businesses may understand which suggestions will result in the most consumers by examining trends in other companies that provide customized recommendations (Wu et al., 2018).

4. NLP

NLP is used in a variety of commercial applications, including e-commerce, healthcare, and advertising.

Translation by Machine

Machine translation, one of the most often utilized NPL applications, provides automated translation without the need for human intervention. MT is very important in commerce since it simplifies communication, allows organizations to reach a wider audience, and quickly and cost-effectively read foreign regulatory papers and communications (Seljan & Dunđer, 2014).

Monitoring of Social Media

Nowadays, social media is playing a critical role in the development of connections between organizations and customers, offering an unparalleled chance to build customer service by obtaining input, answering queries, and collecting feedback (Ramaswamy & DeClerck, 2018). Companies often use social media monitoring solutions that are based on NLP technology to leverage their social media presence (Farzindar & Inkpen, 2015). NLP allows you to monitor social media platforms for mentions of a business and get notifications when they occur. When it comes to preventing bad reviews from destroying reputation and responding quickly to possible crises, NLP technology is critical.

Emotional Analysis

Comprehending a human language may be difficult when it comes to views and feelings. However, cutting-edge sentiment analysis and opinion mining can handle it. Emotion Recognition is an NLP approach for interpreting and categorizing sentiments in subjective information (Drus & Khalid, 2019). In other sense, it can recognize positive and negative emotion in text. You may wish to utilize sentiment analysis to analyze social media mentions and address negative views before they become popular, study customer responses to your goods, and get a comprehensive picture of how people feel about the business (Nanli et al., 2012).

Virtual Assistants

Virtual assistants and virtual assistants are two more excellent NLP application cases. These programs are used to answer questions automatically. Chatbots and virtual agents are programmed to interpret human language and respond appropriately. Even more astounding, AI-powered chatbot and online assistants learn and improve with each contact. It goes without saying that these apps are very beneficial to enterprises (Prajwal et al., 2019). They are available 24 hours a day, seven days a week, and fundamentally shorten response times by processing the majority of enquiries and leaving just the most challenging situations to human agents (Kuligowska & Lasek, 2011).

Text examination

Businesses may discover helpful trends and get significant insights by analyzing texts and extracting different sorts of components from them, such as individuals, dates, and places (Hasan et al., 2019). This surely helps more effective decision and the development of customer-focused initiatives. For instance, online businesses may utilize NLP-powered systems to do text analysis on product evaluations to learn what their customers like and hate about their products, as well as other important information.

Speech Recognition

NLP is used in speech recognition technology to convert spoken speech into a computer form, allowing apps and devices to react to spoken instructions. Voice recognition is a vital part of virtual assistants such as Siri and Alexa. This technology is also impacting companies. To begin with, it may significantly increase company productivity since it is much simpler to juggle using voice rather than keyboard and turn spoken words into written documents. Furthermore, NLP allows businesses to automatically transcribe phone conversations, send emails, and translate. And it's not just for the office: in a business, for example, voice recognition may speed consumer shopping and provide value to the brand.

Text Extraction

Text extraction or information retrieval, is an NLP powered system that locates specified data in a text automatically. It may also extract keywords from text as well as particular properties such as product serial numbers. When combined with sentiment classification, keyword extraction may help business understand which terms customers use the most in bad reviews, making it simpler to spot them. Autocorrect, Spell Check, and Other Features are prevalent in word processing software and text editor tools. Autocorrect detects misspellings and substitutes them with the most similar correct phrases (Kulkarni & Shivananda, 2019). The distinction between spell check and autocorrect is that spell check uses a dictionary, while autocorrect uses pre-entered words. Nevertheless, NLP techniques have progressed beyond spellcheck and proofreader. The cutting-edge NPL writing tools may detect grammatical errors and provide comments about your writing style. Overall, they provide rapid, clear, and accurate interaction, which is critical for organizations today.

In short, organizations are leveraging NLP to better comprehend consumer intent via sentiment analysis, get critical knowledge from unstructured information, enhance communication, and boost overall performance. Without tiring, NLP technology can analyze language-based data quicker than humans. Without a doubt, we can anticipate Natural Language Processing to grow even more significant in the corporate world in the future.

Results from data analysis

The data information and descriptive statistical analysis for the outcome and control variables are shown in table 1 and figure 1. After omitting the missing cases the dataset had size=910. The average score of predictive modelling was the highest among all the features as shown in figure 1. indicating that the predictive analytics was the most implanted feature.

Column	Non-Null Count	Dtype	Role
Predictive Analytics	910 non-null	int64	Feature
AI-powered Chatbots	910 non-null	int64	Feature
ML Recommendations	910 non-null	int64	Feature
NLP Customer Support	910 non-null	int64	Feature
Loyalty	910 non-null	int64	Target

Table 1. Target and features info.

	count	mean	std	min	25%	50%	75%	max
Predictive Analytics	910.00	3.02	1.40	1.00	2.00	3.00	4.00	5.00
AI-powered Chatbots	910.00	2.93	1.44	1.00	2.00	3.00	4.00	5.00
ML Recommendations	910.00	2.94	1.44	1.00	2.00	3.00	4.00	5.00
NLP Customer Support	910.00	2.96	1.40	1.00	2.00	3.00	4.00	5.00
Loyalty	910.00	0.50	0.50	0.00	0.00	1.00	1.00	1.00

Figure 1

Figure 2 illustrates the correlation heatmap. Every row and column in the correlation heatmap represents a feature and a target. The cells illustrate the relationship that exists between all of the characteristics and the target.

The degree of correlation among the variables shown along each axis is displayed in each square. The correlation scale runs from minus one to plus one. When the values are closer to zero, this indicates that there is not a linear relationship between the 2 factors. The degree to which the color's intensity varies serves as a representation of the indicator of correlation. The closer the correlation is to 1, the greater the association between the two variables is. This means that when one variable grows, the other variable also grows, and the closer the correlation is to 1, the greater this association is. A correlation that is closer to -1 is the same as the previous one, but instead of both variables rising when the other grows, one variable will decrease. Since these squares are relating each factor to themselves, the diagonals appear all shaded dark red. This indicates that the correlation is exact. The degree of correlation between two variables is shown by the size of the number and the darkness of the color. As a result of the fact that the same two factors

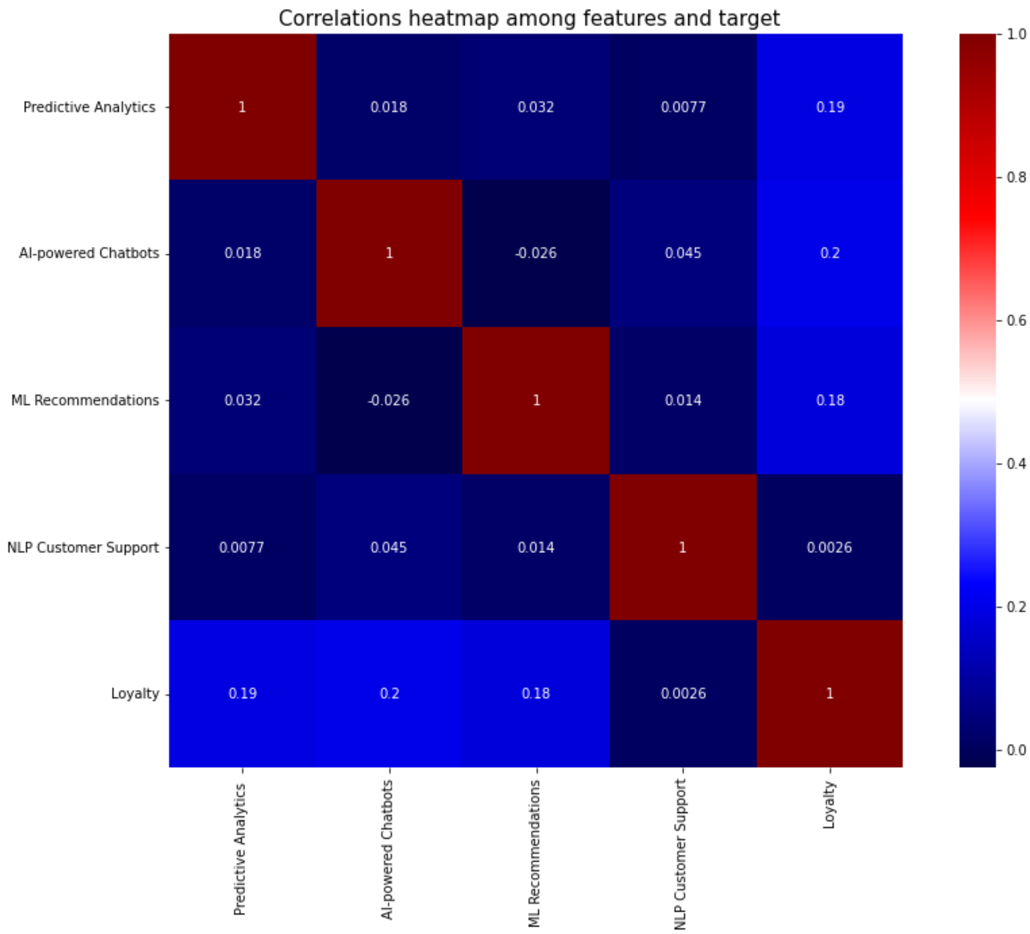

Figure 2

are being grouped together in each of those squares, the plot is likewise symmetrical around the diagonal. We can see from the heatmap that NLP applications have the lowest correlation score. This might indicate the infancy of NLP applications in businesses.

In the process of addressing classification issues, the confusion matrix is a widely used measurement tool. It may be used for situations involving 2 class classification algorithm as well as those involving more than two classes classification. Counts from both the expected and actual values are represented in confusion matrices. The "TN" output, which stands for "True Negative," indicates the quantity of negative cases that have been properly identified. In a similar fashion, "TP" is an abbreviation for "True Positive," which denotes the quantity of positive cases that have been properly identified. The term "FN" refers to a false negative value, that is the quantity of exact positive cases that were categorized as negative; the term "FP" demonstrates a false positive value, which is the quantity of true negative examples that were categorized as positive; and the term "FP" shows a value that shows the quantity of actual positive cases that were classified as negative. When it comes to classification work, accuracy is one of the criteria that is used the most often.

When used to datasets that are not evenly distributed, accuracy might provide deceptive results; hence, there are additional measures that are derived from confusion matrix that can be helpful for analyzing performance.

When comparing multiple models, the confusion matrix is a useful tool for determining how well each model predicted both true positives (TP) and true negatives (TN) (TN).

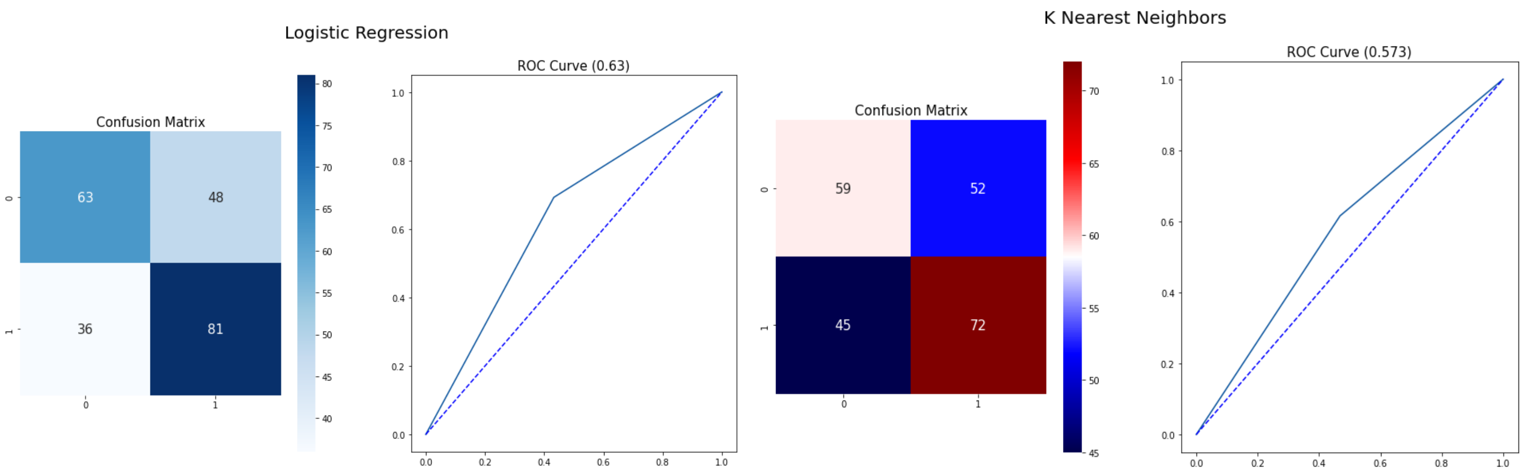

Figure 3

If one model identified a TP as well as TN more accurately than any other model, then we chose to use that model as the foundation for our analysis.

A receiver operating characteristic curve, more often referred to as a ROC curve, is a graph that displays the performance of a classification algorithm over all classification levels. The following two parameters are shown on this curve: Proportion of True Positive, and the Proportion of False Positives.

Drawing the true positive rate on one axis and the false positive rate on another axis results in the construction of a receiver operating characteristic (ROC) curve (FPR). The percentage of positive observations that were properly expected to being positive out of the total number of positive observations is referred to as the true positive rate (TP/(TP + FN)). In a similar manner, the false positive ratio is defined as the percentage of data that are wrongly projected to being positive from all of the negative data (FP/(TN + FP)). On the receiver operating characteristic (ROC) space, a discrete classification that only delivers the predicted class yields a single point. However, for probabilistic classifiers that provide a probability or score indicating the extent to which a point belongs to one category rather than another, we may generate a curve by adjusting the score threshold.

The ROC curve illustrates the tradeoff that must be made between sensitivity, shown by TPR, and specificity, denoted by 1 minus FPR (S. Trivedi & Patel, 2020a). A higher performance may be inferred from classifiers that produce curves that are located closer to the upper left corner. It is reasonable to assume that a random classifier will provide results with points that are located along the diagonal, where, FPR equals TPR. When the curve approaches the diagonal line of the curve at an angle of 45 degrees or closer, the accuracy of the test decreases.

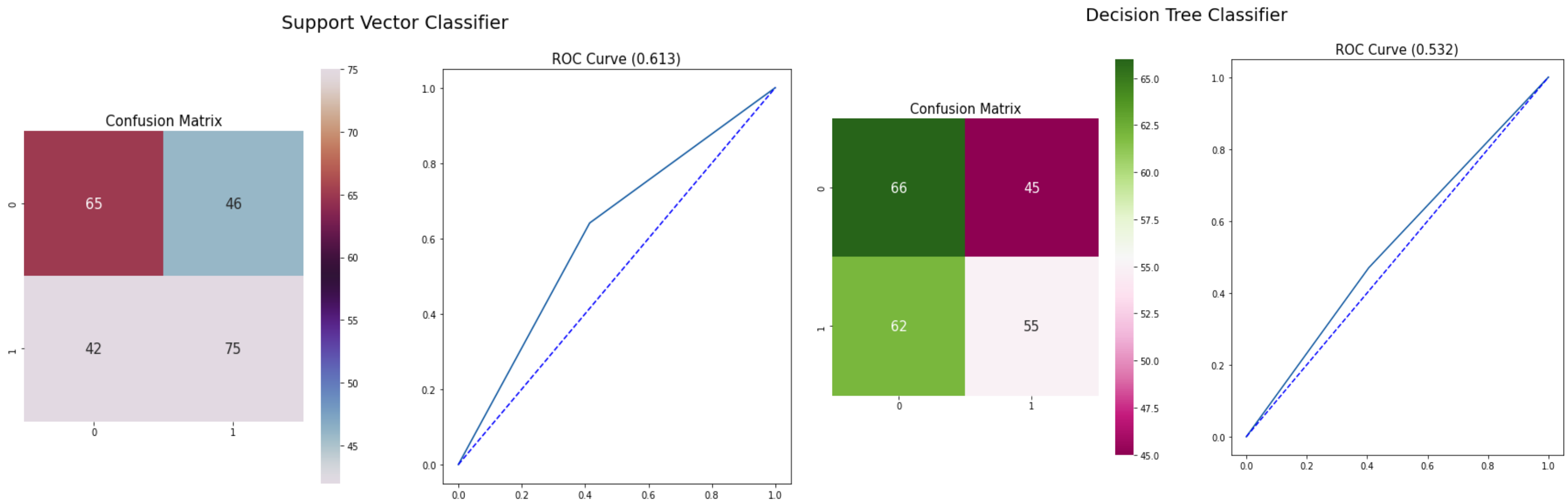

Figure 4

The results of logistic regression and K Nearest Neighbors are reported in figure nn. It can be seen that the True Positives (TP) is 81, the True Negatives (TN) is 63, False Positives (TP) is 48, the False Negatives (FP) is 36. For our model, we have got 0.803. the table further shows that the training accuracy for logistic regression is: 64.809%, the testing accuracy for is: 63.15%, and the F1 score is: 0.658 The training accuracy for KNN is: 70.087 % The testing accuracy for KNN is: 57.456 % The F1 score for K Nearest Neighbors is: 0.573.

The training accuracy for SVC is: 67.30205278592375 % The testing accuracy for SVC is: 61.40350877192983 % The F1 score for Support Vector Classifier is: 0.6302521008403362. The training accuracy for Decision Tree Classifier is: 83.43108504398828 % The testing accuracy for Decision Tree Classifier is: 53.07017543859649 % The F1 score for Decision Tree Classifier is: 0.5069124423963135

The training accuracy for Random Forest Classifier is: 83.43108504398828 % The testing accuracy for Random Forest Classifier is: 53.94736842105263 % The F1 score for Random Forest Classifier is: 0.5606694560669456.

The training accuracy for Ada Boost Classifier is: 65.5425219941349 % The testing accuracy for Ada Boost Classifier is: 64.03508771929825 % The F1 score for Ada Boost Classifier is: 0.6583333333333333

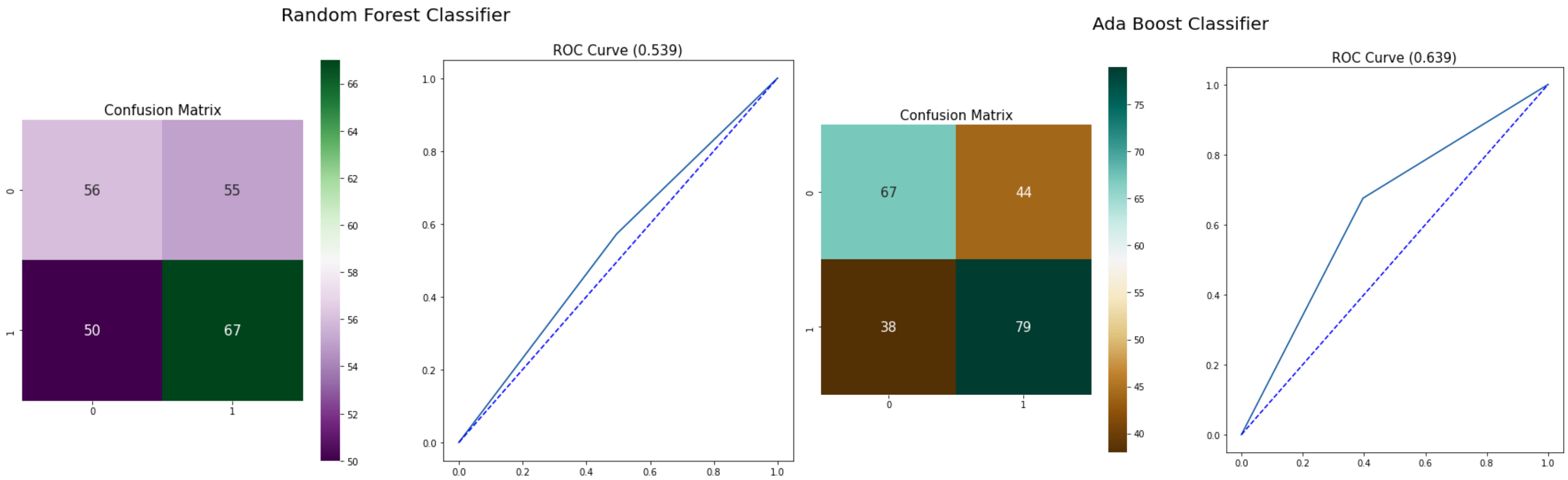

Figure 5

Additionally, we applied two other classifiers, Extra Trees and Bagging Classifier (Figures not shown for brevity) The training accuracy for Extra Trees Classifier is: 83.43108504398828 % The testing accuracy for Extra Trees Classifier is: 50.0 % The F1 score for Extra Trees Classifier is: 0.49557522123893805.

The training accuracy for Bagging Classifier is: 82.99120234604106 % The testing accuracy for Bagging Classifier is: 54.385964912280706 % The F1 score for Bagging Classifier is: 0.5666666666666667.

When using Decision Trees to forecast a label for a data, we begin at the tree's roots in order to make our predictions (S. Trivedi & Patel, 2020b). The Root Node is representative of the complete population or sample, and from there, it is partitioned into two or more sets that are identical to one another. The process of separating a single node to set of sub-nodes is referred to as splitting. The point at which a sub-node decides to branch out into more sub-nodes is referred to as the "decision node." We do a comparison between the entries of the root property and the attribute of the item. Following the path indicated by the comparison, we proceed to the succeeding node after having followed the branch that corresponds to the value in consideration. Gini impurity is used to determine the likelihood that an element that was selected at random would have the wrong classification. This probability is calculated by multiplying the likelihood of selecting an element with the probability of having the wrong classification.

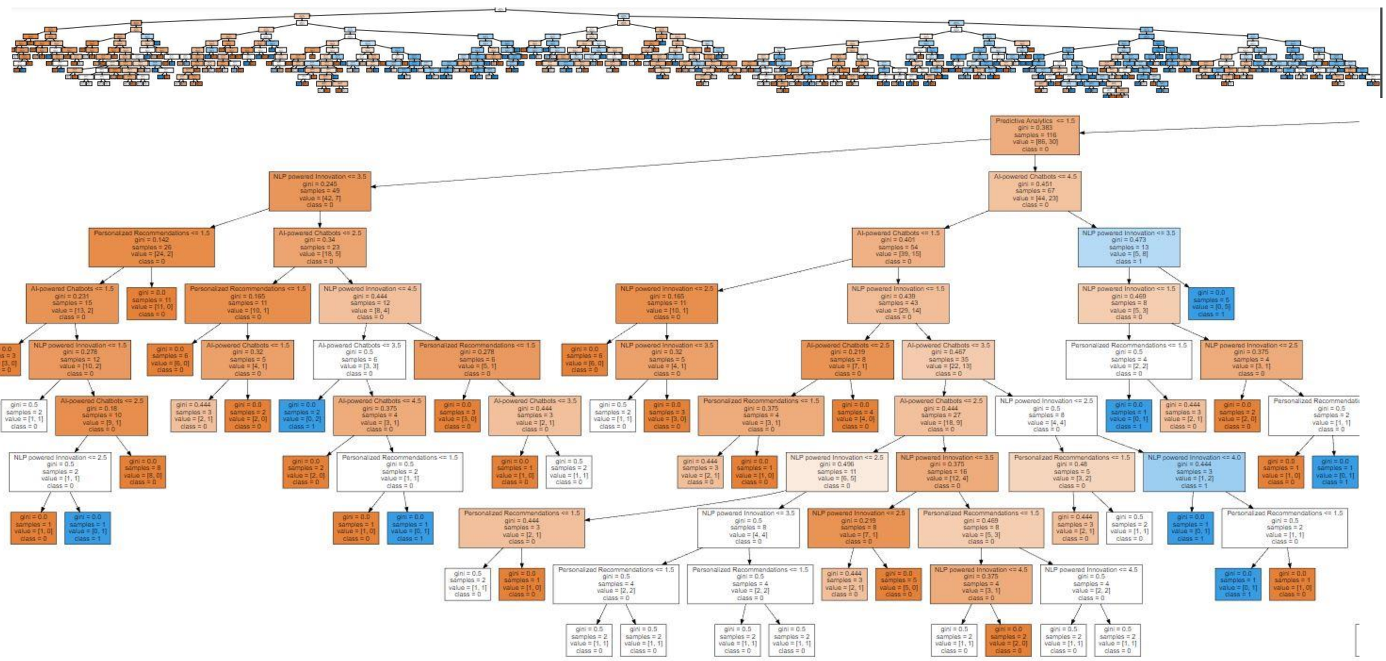

Figure 6

The findings of this research revealed that AI, machine learning, and natural language processing (NLP) technologies should be utilized in customer support, chatbot, predicative modeling, and other technologies use them to engage consumers and monitor their relationships with the company. With the continued transition to digital, providing a highly individualized customer experience for online consumers is critical for building customer loyalty. Product suggestions, in particular, are an excellent approach to customize the customer experience since they assist consumers in discovering goods that fit their interests and preferences.

They should be used to improve the efficiency and effectiveness of operations, and AI is utilized to streamline decision-making tasks. NLP is used to analyze, comprehend, and interpret human language, while ML teaches machines to learn from information and anticipate outcomes. these capabilities may improve the efficiency and effectiveness of corporate operations. They are also utilized to increase the profitability of enterprises. Furthermore, they make firms more competitive. NLP, in conjunction with other ML data processing technologies, has yet to achieve its peak and offers a promising future for organizations across a wide range of sectors.

These three developments will fundamentally alter the corporate world and our way of life. New products will have an impact on how consumers connect with companies, how people work, how we buy, and much more. These technologies enable computers to do activities that previously required human intellect. They have the potential to change the way we engage with technology, allow us to understand new and sophisticated business ideas, and make the customers more loyal.

Conclusion

Health disorders Customer loyalty is an essential component of every organization. It might be the only method to assure that a company's growth persists. Chatbots are a great tool to interact and understand consumers at scale. They cannot, however, address every query client may have. Some are intricate, while others are situational. These questions must still be handled by people. Despite the fact that the chatbot business is expanding, there has been little chatbot adoption. Customers complain that chatbots seem unnatural and insensitive. Companies may change the linguistic style of a chatbot to make it more personalized. Human-like chatbots increase customer pleasure and trust, resulting in more chatbot adoption. As a result, the function of anthropomorphism and chatbots' perceived social presence should be investigated further. Furthermore, some clients face privacy dilemmas as a result of personalization. Companies should strike a balance for consumers' personal information and reveal it in return for an offer.

Personalization and machine learning are not new concepts. They have been used for decades, but the big change now is that these are getting used extensively. Organizations all over the world are discovering the value of reaching closer to their consumers and offering recommendations that will help them generate more loyal customers. Businesses must also understand that while providing individualized suggestions to prospective clients or consumers, they must ensure that their suggestions are appropriate. The finest recommendations are those that are tailored to a particular demand. A suggestion that drives a company owner to an affiliate website, for example, is a kind of targeted advertising. This kind of advertising has been utilized effectively for many years, and company owners should continue to use it in order to improve the percentage of people who visit their websites.

As humans' reliance on computer-assisted systems grows, researchers are concentrating on more effective technologies that can simulate human interactions while also understanding human languages and emotions and feelings. The issue of information explosion has resulted in a surge of unstructured text, which is regarded useless in all sectors, including finance, healthcare, and education. In this respect,NLP is one of the innovative techniques that may be used with sophisticated deep learning, and machine learning to improve the rate of understanding and processing natural language. This may improve human-computer interaction and allow for the analysis and structuring of massive amounts of useless and unprocessed data/text in a variety of businesses. This will provide relevant results that will improve decision-making and consequently operational efficiency.

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