



Enhancing Customer Relationship Management through Sentiment Analysis and Social Media Data Mining

Esmeralda Kazia¹, Bledar Kazia²

Department of Computer and Applied Sciences, Barleti University, Tirana, Albania

Software Engineering Department, Canadian Institute of Technology, Tirana, Albania

Emails: e.kazia@umb.edu.al ; bledi.kazia@cit.edu.al

Abstract

Customer Relationship Management (CRM) is a crucial aspect of modern business that enables companies to maintain healthy relationships with their customers. In today's digital age, customers interact with companies through multiple channels, including social media, email, and phone. Therefore, analyzing customer feedback and sentiment has become increasingly important in understanding their needs and improving the overall customer experience. To this end, this work proposes a new system that applies deep learning for sentiment analysis in a way that improves the performance of CRM by analyzing customer feedback from various sources, companies can gain valuable insights into customer needs and preferences and identify areas for improvement in their products and services. Then, we present a case study of a company that implemented the proposed system in its CRM strategy. The results showed that our system could improve customer satisfaction and retention rates and enable the company to identify and address customer concerns more efficiently. Our approach can be applied as a powerful tool to enable companies to gain valuable insights into customer needs and preferences, identify areas for improvement in their products and services, and develop targeted marketing campaigns and personalized communication strategies.

Keywords: Sentiment Analysis; Customer Relationship; Management; Social Media Analysis

1. Introduction

Customer Relationship Management (CRM) refers to the strategies, practices, and technologies used by businesses to manage and analyze customer interactions and data throughout the customer lifecycle. The goal of CRM is to improve customer satisfaction, loyalty, and retention, ultimately leading to increased revenue and profitability for the business. CRM systems typically include features for tracking customer interactions and data, such as sales activity, customer service inquiries, and marketing campaigns. This data is then used to segment customers, analyze their behaviors and preferences, and personalize interactions with them. Effective CRM requires a customer-focused approach, with a deep understanding of customer needs and desires. It also requires collaboration across departments, such as sales, marketing, and customer service, to ensure a seamless customer experience. CRM systems can be implemented in a variety of industries and businesses, including retail, healthcare, finance, and more. Common CRM software providers include Salesforce, Microsoft Dynamics, and HubSpot, among others.

Sentiment analysis is a technique that involves using natural language processing (NLP) and machine learning (ML) algorithms to analyze customer feedback and identify the sentiment behind it. In the context of CRM, sentiment analysis can be used to enhance customer interactions and improve customer satisfaction. By analyzing customer feedback, businesses can gain insights into customer opinions, preferences, and pain points, which can be used to inform product development, marketing strategies, and customer service. One way sentiment analysis can be used in

CRM is to analyze customer service interactions. By analyzing customer service calls, emails, or chats, businesses can identify trends in customer feedback, such as common issues or complaints. This information can then be used to develop solutions to these issues and improve the customer experience. Sentiment analysis can also be used to identify positive feedback from customers, which can be used to identify areas of strength in the business and inform marketing campaigns.

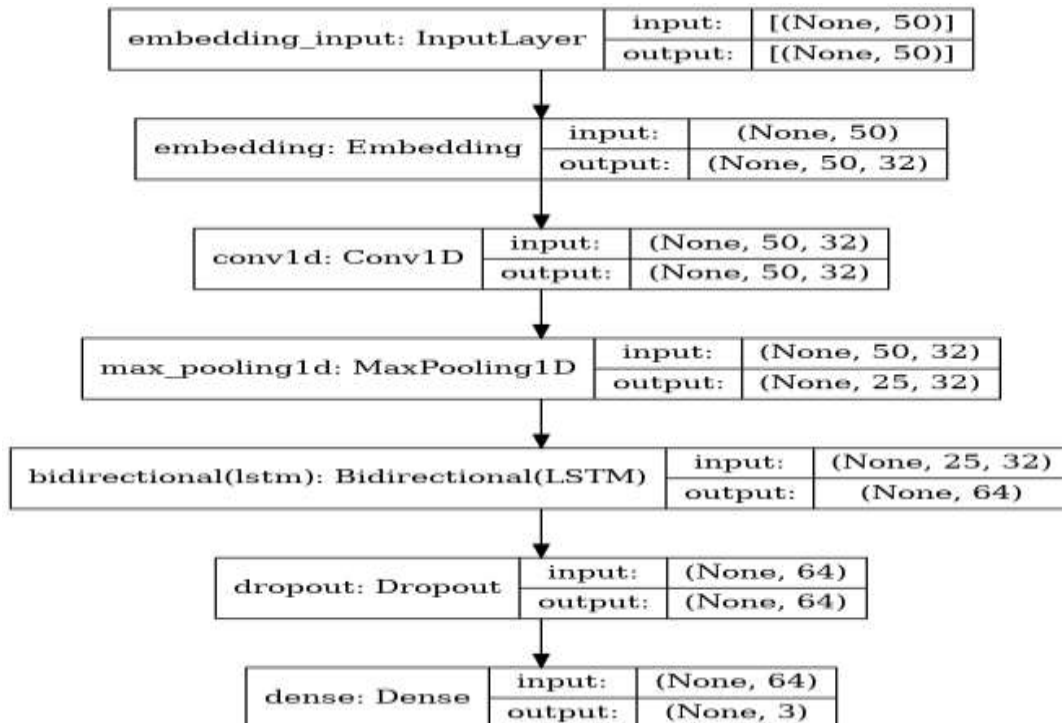
Another way sentiment analysis can enhance CRM is by analyzing customer feedback on social media. Customers often turn to social media to share their experiences with businesses, and sentiment analysis can help businesses identify and respond to these comments in a timely and effective manner. By monitoring social media sentiment, businesses can identify potential issues or opportunities and take action to improve the customer experience. This can also help businesses to engage with customers in a more personalized and effective way, which can lead to increased customer loyalty and satisfaction. In this work, we introduce an improved deep learning system that promotes the performance of CRM based on social feedback. Our system integrated a convolutional model to extract textual features from social tweets, then, the bidirectional recurrent module is applied to learn the contextual dependencies between text elements. Then, the proposed system can be used to provide insights to improve the overall CRM analysis. The remainder of this work is planned as follows. Section 2 discusses and analyzes the literature. Section 3 presents the methodology of the proposed system for improving the CRM. The experimental part and results are discussed in section 4. Section 5 provides a summary conclusion of this study.

2. Related Studies

The literature on sentiment analysis for enhancing CRM suggests that sentiment analysis can be a valuable tool for businesses to improve their customer experience. By analyzing customer feedback from various sources, including social media, businesses can identify customer sentiment, pain points, and preferences. This information can be used to develop targeted marketing campaigns, improve products and services, and enhance the overall customer experience. For example, in [1], the authors explored the use of sentiment analysis to improve social CRM (SCRM). They explained how sentiment analysis can be used to analyze customer feedback on social media, enabling companies to gain insights into customer preferences, concerns, and satisfaction levels. They also discussed how sentiment analysis can help companies better understand customer sentiment and take appropriate actions to improve customer engagement and loyalty. In [2], the authors studied how AI can be used to gather and analyze customer data to generate automated insights, such as identifying customer preferences, predicting customer behavior, and recommending products and services. They also discussed how AI-powered chatbots can be used to provide personalized customer service and support, improving customer engagement and loyalty. In [3], the authors investigated the application of sentiment analysis with an artificial intelligence (AI) approach to boost business performance through analysis of users' sentiment in customer feedback on social media, enabling companies to understand customer sentiment towards their products or services. They also discussed how AI can be used to analyze large volumes of customer data to identify patterns and make predictions about customer behavior, helping companies make informed business decisions. They introduced many case studies demonstrating the effectiveness of sentiment analysis and AI in improving business performance, including increasing sales and improving customer satisfaction. In [4], the authors debated the advancements and new avenues in the field of opinion mining and sentiment analysis by describing how opinion mining and sentiment analysis have progressed from simple text classification techniques to more sophisticated approaches that incorporate natural language processing, machine learning, and knowledge representation. They highlighted the challenges and opportunities presented by the growing availability of data on social media and the internet, and how opinion mining and sentiment analysis can be used to analyze this data to gain insights into public opinion and behavior. Additionally, they explored the potential applications of opinion mining and sentiment analysis in various fields, such as marketing, politics, and healthcare. In [5], the authors surveyed the data mining techniques and their applications in marketing, sales, and CRM by describing in which way the data mining could be used to analyze customer data to identify patterns, make predictions, and gain insights into customer behavior, preferences, and needs. They addressed various data mining techniques, such as decision trees, neural networks, and association rules, and explained how they can be applied to solve real-world marketing and CRM problems. They also discussed the ethical and legal implications of data mining and provided guidance on how to implement data mining projects successfully. In [6], the authors describe how CRM mechanisms could be used to manage customer interactions and improve customer satisfaction, loyalty, and retention. They covered different CRM mechanisms, such as customer profiling, segmentation, and targeting, and discussed their advantages, limitations, and implementation challenges. They also identified gaps in the existing literature and provided recommendations for future research, such as the need for more empirical studies, the integration of multiple CRM mechanisms, and the consideration of cultural and contextual factors in CRM implementation. In [7], the authors described how sentiment

analysis can be used to extract information from online reviews about the consumers' attitudes and opinions towards a product. They also combined this information with historical sales data to develop a forecasting model based on the Bass diffusion model. They demonstrated the effectiveness of the proposed method using data from a popular mobile phone brand and showed how it can improve the accuracy of sales forecasts compared to traditional methods. They also studied the practical implications of their method for product managers and marketers, such as the ability to monitor and respond to changes in consumer sentiment in real-time. In [8], the authors described the different tasks involved in opinion mining, such as opinion extraction, sentiment classification, and opinion summarization, and the various approaches used to perform these tasks, such as rule-based, statistical, and machine learning-based methods. They also debated the applications of opinion mining and sentiment analysis in various domains, such as marketing, politics, and healthcare, and discussed the challenges and future directions of the field. In [9], the authors developed a sentiment analysis for an approach to improving CRM based on incremental learning that could adapt to these social changes over time. They demonstrated the effectiveness of their proposed approach using data from a major airline company and showed how it can improve the accuracy of sentiment analysis compared to traditional methods. They also discussed the practical implications of their approach for CRM, such as the ability to monitor and respond to changes in consumer sentiment in real-time. In [10], the authors explored the challenges of sentiment analysis in the Turkish language, such as the complex morphology and the lack of annotated datasets, and proposed a multi-stage approach to overcome these challenges. Then, they developed a framework that combines pre-processing steps to normalize the text, feature extraction and selection, and sentiment classification algorithms. They demonstrated the effectiveness of the proposed framework using a dataset of customer feedback from a major Turkish telecommunications company. The authors showed that their approach achieves high accuracy in sentiment classification and topic categorization, outperforming existing approaches. In [11], the authors reviewed the challenges and opportunities of sentiment analysis in the context of UGC, including the complexity of natural language and the need for accurate sentiment classification. They proposed a three-stage approach for sentiment analysis, which includes pre-processing, feature extraction, and sentiment classification algorithms. Their approach was tested on a dataset of hotel reviews, and the results demonstrate the effectiveness of sentiment analysis for extracting decision-relevant knowledge from UGC, such as identifying the strengths and weaknesses of hotels and predicting customer satisfaction.

Figure 1: Illustration of the proposed model for customer sentiment analysis to improve the CRM.



3. Methodological Design

This section introduces a methodology for the proposed sentiment analysis system to improve the performance of CRM in modern business. The methodology involves collecting customer feedback from various sources, such as social media, email, and phone calls, and using sentiment analysis techniques to analyze the sentiment of the feedback. The first step in the methodology is to identify the sources of customer feedback and develop a system for collecting and storing the feedback data.

The next step is to preprocess the customer feedback data, including text cleaning, tokenization, and stemming. This involves removing any irrelevant data, such as noise and stop words, and converting the data into a format that can be analyzed by sentiment analysis algorithms.

Once the data is preprocessed, the proposed deep learning algorithms can be applied to determine the sentiment of the feedback, whether positive, negative, or neutral. The architecture of the proposed model is shown in Figure 1. Convolutional Neural Networks (CNNs) can be used for feature extraction in sentiment analysis for CRM applications. The CNN architecture in our system typically consists of an embedding layer, one or more convolutional layers, a pooling layer, and one or more fully connected layers. The embedding layer maps each word in the input text to a vector representation. The convolutional layer applies filters to the embedding layer's output to extract local features. The pooling layer reduces the dimensionality of the extracted features. The convolutional operation is given as follows:

$$(f * g)(x) = \int_{-\infty}^{\infty} f(t)g(x - t)dt. \quad (1)$$

Then, LSTM is commonly used to handle sequential characteristics in text. The LSTM network consists of memory cells that can store information over a long period, allowing the network to handle long-term dependencies. The calculation of LSTM is as follows:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \quad (2)$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \quad (3)$$

$$c_t = f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (4)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \quad (5)$$

$$h_t = o_t \tanh(c_t) \quad (6)$$

Bidirectional LSTM (BLSTM) is applied here, to extend the LSTM architecture by processing the input sequence in both forward and backward directions, allowing the network to capture context from both past and future data points. In sentiment analysis, a bidirectional LSTM network can be trained on a dataset of text data with labeled sentiment. The network processes the input text data sequentially, and at each time step, it updates the hidden state based on the previous hidden state, and the current input. The advantage of bidirectional LSTM for sentiment analysis is that it can capture the context of the text data and handle complex sentence structures, including negation, sarcasm, and irony. This makes it a powerful tool for analyzing customer feedback and social media data, where sentiment can be difficult to discern.

$$\vec{h}_t = \overrightarrow{LSTM}(m_t) \quad (7)$$

$$\overleftarrow{h}_t = \overleftarrow{LSTM}(m_t) \quad (8)$$

$$h_t = [\vec{h}_t, \overleftarrow{h}_t] \quad (9)$$

After the sentiment analysis is completed, the data is visualized and analyzed to identify trends and patterns in customer sentiment. This can be done using data visualization tools such as charts, graphs, and heat maps. Finally, the insights gained from sentiment analysis are used to develop targeted marketing campaigns and personalized communication strategies that address customer concerns and preferences. This enables companies to improve customer satisfaction and retention rates and gain a competitive advantage in their industry.

4. Experimental Analysis

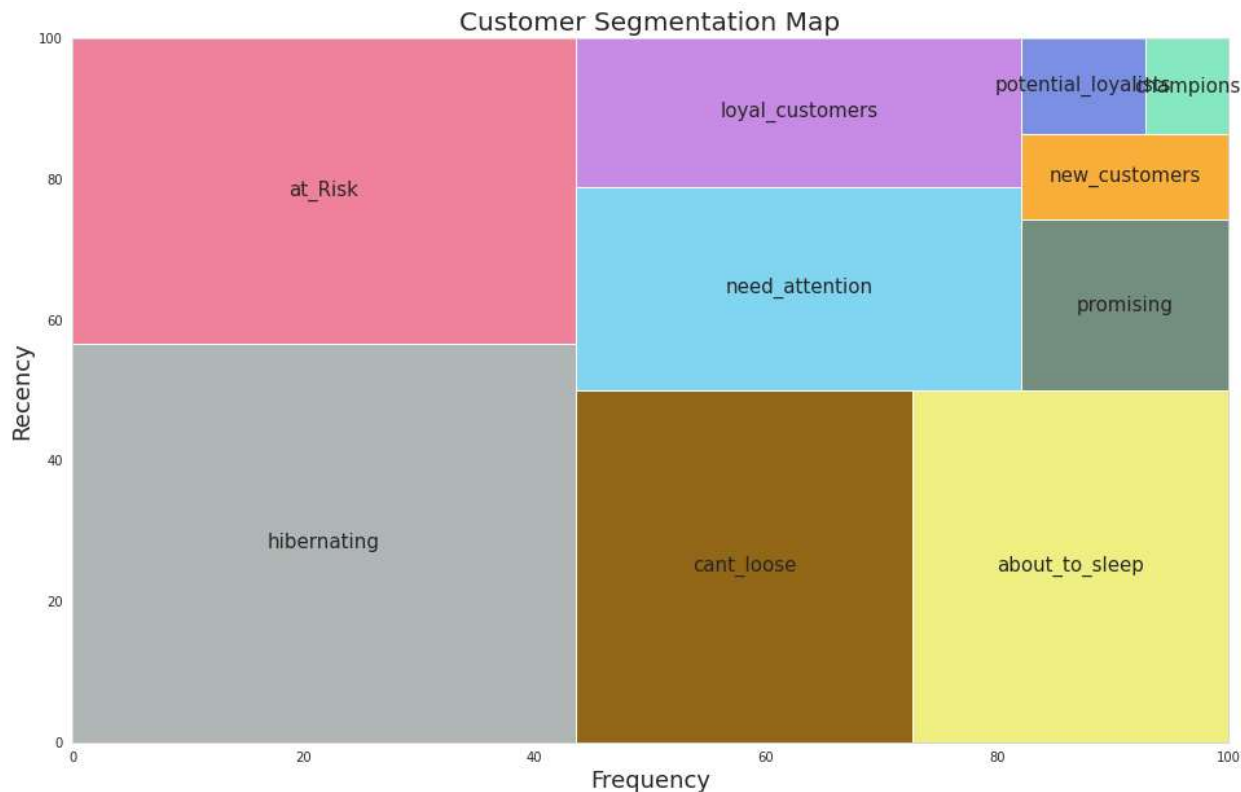


Figure 2: Illustration of the custom segmentation map in our RFM analysis.

A CRM dataset typically includes information about customers, their interactions with the company, and their purchasing behavior. In this study, we use an E-commerce dataset from UCI machine learning¹ to experiment with the proposed model. The data contain Customer contact information, Customer demographics, Customer interactions, Customer purchase history, Customer preferences, and Customer satisfaction. For a non-store internet retailer situated in the United Kingdom, this dataset included all sales made between December 1, 2010, and December 9, 2011. Personalized presents for any event are the company's mainstay. The company serves a large number of wholesalers.

RFM analysis is a method of analyzing customer behavior that groups customers based on their transaction history. RFM stands for Recency, Frequency, and Monetary value, which are the three key factors used to segment customers. Recency indicates how recently a customer has made a purchase. Customers who have made a purchase more recently are generally considered more valuable because they are more likely to make another purchase soon. Frequency implies how often a customer makes purchases. Customers who make purchases more frequently are generally considered more valuable because they have a higher lifetime value to the company. Monetary value indicates how much money a customer has spent on purchases. Customers who have spent more money are generally considered more valuable because they have a higher overall value to the company. To conduct an RFM analysis, we calculate these three metrics for each customer. Then, the customers are segmented into different groups based on their RFM scores (see Figure 2). By segmenting customers based on their RFM scores, we can develop more targeted marketing and sales strategies, such as personalized promotions or loyalty programs. The displayed RFM analysis can be used to identify customers who are at risk of leaving and develop retention strategies to keep them engaged.

Table 1: numerical results of segmentation analysis.

| | recency | | | | monetary | | | | frequency | | | |
|-----------------------|---------|-------|-------|--------|----------|-------|-------|--------|-----------|------|------|------|
| | max | std | min | mean | max | std | min | mean | max | std | min | mean |
| about_to_sleep | 74.00 | 10.95 | 35.00 | 53.32 | 74.00 | 10.95 | 35.00 | 53.32 | 4.00 | 0.38 | 3.00 | 1.17 |
| at_Risk | 375.00 | 68.62 | 74.00 | 153.79 | 375.00 | 68.63 | 73.00 | 153.79 | 7.00 | 0.96 | 4.00 | 2.88 |

¹ <http://archive.ics.uci.edu/ml/index.php>

| | | | | | | | | | | | | |
|----------------------------|--------|-------|-------|--------|--------|-------|-------|--------|--------|-------|------|-------|
| cant_loose | 373.00 | 65.25 | 73.00 | 132.97 | 374.00 | 65.25 | 73.00 | 132.97 | 35.00 | 4.30 | 7.00 | 8.38 |
| champions | 15.00 | 3.69 | 1.00 | 6.37 | 13.00 | 3.68 | 1.00 | 6.36 | 210.00 | 16.48 | 5.00 | 12.43 |
| hibernating | 376.00 | 92.02 | 73.00 | 217.61 | 375.00 | 92.01 | 74.00 | 217.61 | 3.00 | 0.31 | 3.00 | 1.10 |
| loyal_customers | 72.00 | 15.58 | 17.00 | 33.61 | 72.00 | 15.58 | 17.00 | 33.61 | 63.00 | 4.55 | 3.00 | 6.49 |
| need_attention | 72.00 | 11.55 | 36.00 | 52.44 | 72.00 | 11.56 | 34.00 | 52.44 | 3.00 | 0.48 | 3.00 | 2.33 |
| new_customers | 15.00 | 3.91 | 3.00 | 7.43 | 15.00 | 3.91 | 3.00 | 7.43 | 2.00 | 0.01 | 2.00 | 1.00 |
| potential_loyalists | 34.00 | 9.34 | 2.00 | 17.40 | 34.00 | 9.34 | 2.00 | 17.41 | 3.00 | 0.65 | 2.00 | 2.02 |
| promising | 34.00 | 5.25 | 17.00 | 23.43 | 34.00 | 5.20 | 16.00 | 23.51 | 1.00 | 0.01 | 1.00 | 1.00 |

More, we conduct RFM segment analysis to identify and group customers with similar characteristics or needs, in a way that allows the creation of marketing campaigns and personalized communication strategies to better serve their customers. The numerical results of the segment analysis are given in Table 1. The results enable us to identify the most profitable customers and tailor their marketing efforts to these groups, resulting in more effective campaigns and higher customer satisfaction.

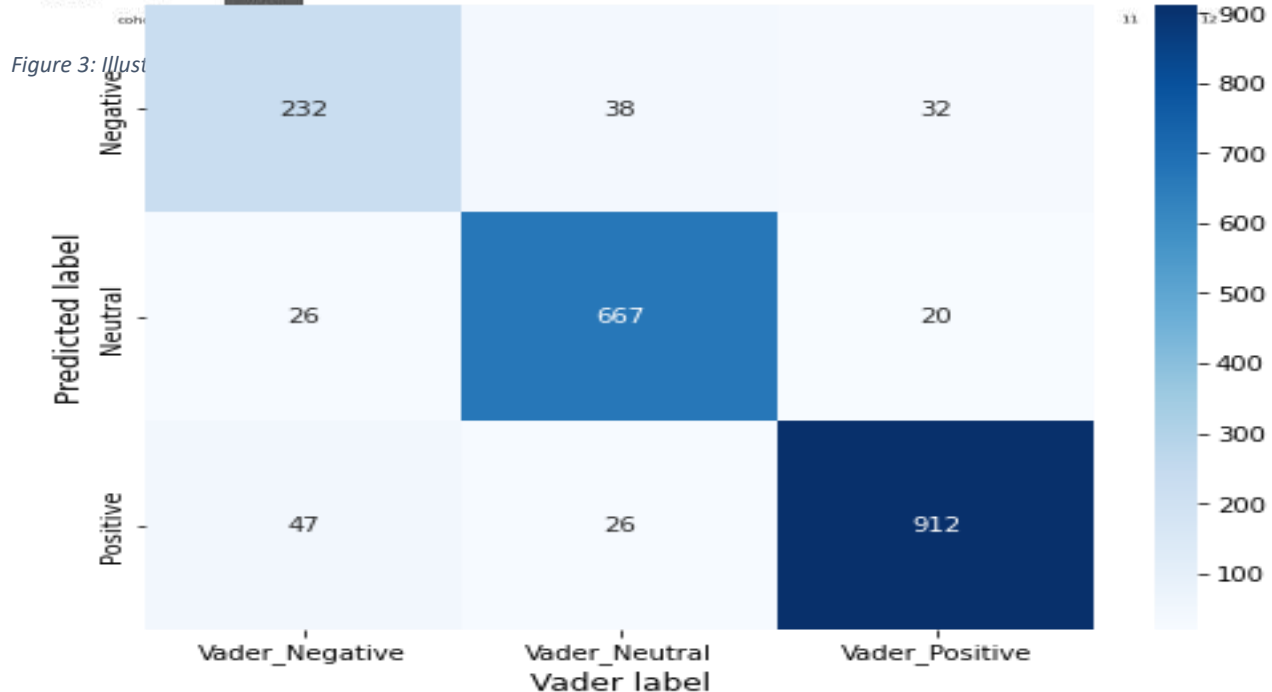
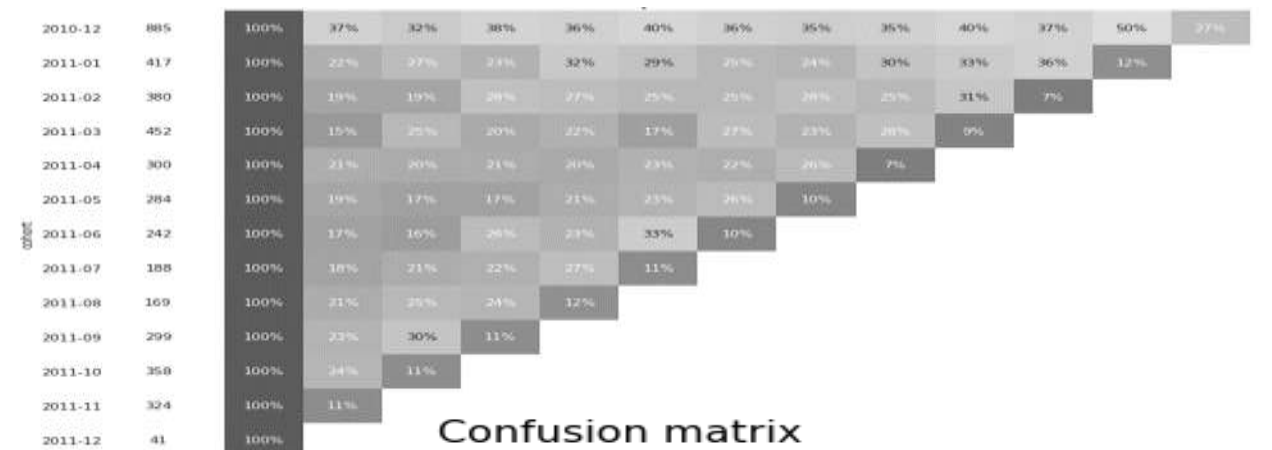


Figure 4: confusion matrix of the proposed system

Further, we conduct cohort analysis as a method for analyzing customer behavior and patterns over time. It involves grouping customers who share a common characteristic, such as those who made their first purchase in a particular month or quarter, and then tracking their behavior and spending over subsequent periods (see Figure 3). The goal of cohort analysis is to better understand how different groups of customers behave over time and to identify trends and patterns in customer behavior. By analyzing these patterns, companies can develop targeted marketing strategies and improve their customer retention rates.

A confusion matrix, presented in Figure 4, is a useful tool for evaluating the performance of a sentiment analysis system in CRM. The confusion matrix provides a summary of the predicted sentiment labels compared to the actual sentiment labels in the test data. The matrix is typically represented as a table with four entries: True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The results show that the proposed system can classify the user's sentiment precisely.

5. Conclusions

In this work, we propose a simple but efficient sentiment analysis system, that acts as a powerful tool for improving the performance of CRM in modern business. By analyzing customer feedback and sentiment from various sources, including social media, email, and phone calls, companies can gain valuable insights into customer needs and preferences, identify areas for improvement in their products and services, and develop targeted marketing campaigns and personalized communication strategies. The case study presented in this paper demonstrates the effectiveness of the proposed system in improving customer satisfaction and retention rates. The company can use our system to analyze customer feedback from social media, email, and phone calls and develop targeted marketing campaigns and personalized communication strategies based on the insights gained. The results showed a significant improvement in customer satisfaction and retention rates, highlighting the potential of sentiment analysis in improving the performance of CRM.

References

- [1] Nasr, M. M., Shaaban, E. M., & Hafez, A. M. (2017). Enhancing Social Customer Relationship Management by Using Sentiment Analysis. *International Journal of Science and Research*, 6, 803-807.
- [2] Deb, S. K., Jain, R., & Deb, V. (2018, January). Artificial intelligence—creating automated insights for customer relationship management. In *2018 8th international conference on cloud computing, data science & engineering (Confluence)* (pp. 758-764). IEEE.
- [3] Ahmed, A. A. A., Agarwal, S., Kurniawan, I. G. A., Anantadjaya, S. P., & Krishnan, C. (2022). Business boosting through sentiment analysis using Artificial Intelligence approach. *International Journal of System Assurance Engineering and Management*, 13(Suppl 1), 699-709.
- [4] Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2013). New avenues in opinion mining and sentiment analysis. *IEEE Intelligent systems*, 28(2), 15-21.
- [5] Berry, M. J., & Linoff, G. S. (2004). *Data mining techniques: for marketing, sales, and customer relationship management*. John Wiley & Sons.
- [6] Soltani, Z., & Navimipour, N. J. (2016). Customer relationship management mechanisms: A systematic review of the state of the art literature and recommendations for future research. *Computers in Human Behavior*, 61, 667-688.
- [7] Fan, Z. P., Che, Y. J., & Chen, Z. Y. (2017). Product sales forecasting using online reviews and historical sales data: A method combining the Bass model and sentiment analysis. *Journal of business research*, 74, 90-100.
- [8] Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: tasks, approaches and applications. *Knowledge-based systems*, 89, 14-46.
- [9] Capuano, N., Greco, L., Ritrovato, P., & Vento, M. (2021). Sentiment analysis for customer relationship management: an incremental learning approach. *Applied Intelligence*, 51, 3339-3352.
- [10] Seyfioğlu, M. S., & Demirezen, M. U. (2017, September). A hierarchical approach for sentiment analysis and categorization of Turkish written customer relationship management data. In *2017 Federated Conference on Computer Science and Information Systems (FedCSIS)* (pp. 361-365). IEEE.
- [11] Schmunk, S., Höpken, W., Fuchs, M., & Lexhagen, M. (2013). Sentiment analysis: Extracting decision-relevant knowledge from UGC. In *Information and Communication Technologies in Tourism 2014: Proceedings of the International Conference in Dublin, Ireland, January 21-24, 2014* (pp. 253-265). Springer International Publishing.

- [12] AL-Rubaiee, H. S., Alomar, K., Qiu, R., & Li, D. (2018). Tuning of Customer Relationship Management (CRM) via Customer Experience Management (CEM) using sentiment analysis on aspects level.
- [13] Ledro, C., Nosella, A., & Vinelli, A. (2022). Artificial intelligence in customer relationship management: literature review and future research directions. *Journal of Business & Industrial Marketing*.
- [14] Plaza, L., & de Albornoz, J. C. (2012). Sentiment analysis in business intelligence: a survey. In *Customer Relationship Management and the Social and Semantic Web: Enabling Clients' Interactions* (pp. 231-252). IGI Global.
- [15] Păvăloaia, V. D., Teodor, E. M., Fotache, D., & Danileț, M. (2019). Opinion mining on social media data: sentiment analysis of user preferences. *Sustainability*, 11(16), 4459.
- [16] Hernes, M. (2015). Performance evaluation of the customer relationship management agent's in a cognitive integrated management support system. In *Transactions on Computational Collective Intelligence XVIII* (pp. 86-104). Springer Berlin Heidelberg.
- [17] Younis, E. M. (2015). Sentiment analysis and text mining for social media microblogs using open source tools: an empirical study. *International Journal of Computer Applications*, 112(5).
- [18] Nadeem, M. (2012). Social customer relationship management (SCRM): How connecting social analytics to business analytics enhances customer care and loyalty?. *International journal of business and social science*, 3(21).
- [19] Umamaheshwari, S., Harikumar, K., & Allinjoie, D. (2021, October). Customer Relationship Management using Sentimental Analysis. In *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)* (pp. 1-6). IEEE.