Transformative Approaches to Customer Sentiment Analysis and Customer Feedback Scoring in CRM Platforms

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***Abstract*—This study introduces an innovative system designed to predict customer satisfaction scores through the integration of sentiment analysis of customer feedback alongside all related factors from a Customer Relationship Management (CRM) system. The system implements the latest transformer models like BERT and RoBERTa then assess customer sentiment using an ensemble learning voting mechanism for accurate sentiment classification, and adaptive customer satisfaction rating. The model generates baseline scores dynamically, based on factors like customer loyalty, and frequency of interactions with the firm, thus enhancing accuracy and relevance when assessing satisfaction. The system is also developed to utilize Turkish data optimizing usage in market shares for firms serving that user group. Empirical results indicate that the ensemble learning approach significantly improves the accuracy of sentiment analysis and the reliability of satisfaction quantification. This resource provides additional contribution to the CRM literature by providing a credible and scalable mechanism to assess customer satisfaction to potentially be implemented in practice across industries. Future work will focus on extending the system's scalability and enhancing its predictive capabilities across diverse sectors.**

Keywords—Customer Relationship Management (CRM), Customer Satisfaction Scoring, Sentiment Analysis, Natural Language Processing (NLP), Transformer Models, Ensemble Learning,Turkish Language Processing, Dynamic Scoring Algorithm

I. Introduction

In the contemporary business context, the customer is acknowledged as a pivotal factor in the pursuit of a sustainable competitive advantage and enhanced business performance. The extant literature suggests that customer satisfaction with a specific brand not only drives customer loyalty to that brand, but also attracts new potential customers, consequently generating increased revenue and overall profits for any company. It is therefore imperative that a comprehensive and systematic analysis of customer satisfaction is conducted prior to the development of any business strategy. The majority of integrated customer feedback systems have employed conventional mechanisms that are either wholly manual or partially automated. Such methods are labour-intensive and therefore susceptible to human error, particularly in relation to the extensive scope of work and detail inherent to customer feedback. Technological advancements, especially regarding artificial intelligence and data science in general [6], are progressing at a faster rate than other fields, greatly improving, speeding up and optimising the processes used to analyse customer feedback. This research aims to create a fully automated system for the assessment of customer feedback. The methods of Natural Language Processing (NLP) and Voting, an ensemble learning technique, have been applied for sentiment analysis using different models available on the Hugging Face platform. The outcomes of these analyses are incorporated together with other important parameters, such as customer loyalty and customer engagement scores, when carrying out customer scoring. These scores can be easily computed by the customer management units, allowing for the tailoring of campaigns and services to customers identified as potential churners. The key contributions of the research are summarized as follows:

- Developed a new model for customer satisfaction scoring that combines the characteristics of new generation transformer models and combines ensemble methods by means of the Voting mechanism to conduct more precise sentiment analysis.
- Implemented a system that varies customer satisfaction scores depending on a customer's loyalty, activity, and sentiments, ensuring that the scales are tailored to the customer at that moment.
- The system architecture is suitable for different customer types, offering comprehensive and flexible solutions covering a wide range of customers and situations.

The structure of the rest of the paper is as follows: The following section will provide a review of current techniques and methods used in the literature with the relevant background. The next section describes the methodology and scoring methodology of the proposed system, with attention to the specific customer satisfaction scoring processes. The Results section presents the results of the system and demonstrates the assessment of customer satisfaction across various categories. In closing, a summary of the outcomes and potential implications of the discoveries are discussed.

II. Related Work

Sentiment analysis and satisfaction scoring methodologies have become increasingly useful techniques for broader CRM

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activities relating to the measurement and assessment aspects of customers in the Customer Relationship Management (CRM) systems. Researchers in the area has worked towards the extraction of sentiment from textual information, the analysis of sentiment in different languages, use of ensembles methods and assessment of the customer satisfaction levels over time. There has been a shift from the mere algorithms to entrenched and integrated systems in the context of sentiment analysis. VADER [8] or TextBlob [11] are rule-based systems that provide straightforward and rapid responses to questionnaires but have very poor comprehension of complexity in language. To counter such incidences, there has been a move towards the use of BERT [4] or Roberta [10] based systems amongst other transformer based approaches. These processes model a certain context which improves the accuracy of the predictive tasks because these processes have been trained using vast reputable resources of data. Ensemble learning strategies have emerged as a prospective path forward to improving performance for sentiment analysis. Rokach [15] showed that taking the outputs of different models as an ensemble allows the shortcomings of any one model to be mitigated. This has been shown to work in various situations in which the sentiment analysis was multilingual or produced complex sentiments from an analysis perspective [2]. For sentiment analysis, of course, no analysis of customer satisfaction would be complete without considering other metrics. Fang and Zhan [5] pointed out that other metrics, like frequency of interactions and historical interactions with customers, should remain a primary consideration in any additional conclusions. Zhang et al. [17] showed that when additional metrics are collected and presented with sentiment analysis or sentiment analysis objectives, understanding of customer satisfaction can expand from a unidirectional metric to a more robust and dynamic metric.

Real-time sentiment analysis has become quite indispensable in improving the efficiency and effectiveness of CRMs. Jiang et al. [9] conducted a research mentioning how crucial it is to engage properly with the clients once they have raised their concerns. This approach enhances customer service strategies considerably. However, this is common for morphologically rich languages such as Turkish. Çoban et al. [3] constructed a Turkish language model designed for sentiment analysis of the twitter posts, and exhibited that language properties can affect the model performance. Customer satisfaction scoring techniques based on sentiment analysis are going to enhance CRMs leading to an emergence of new ideas. Poria et al. [14] investigated the possibility of reception of such a questionnaire in combination with the indicators on the sentiment analysis and proposed a new, more systematic evaluation of customer satisfaction. These developments illustrate the potential advantages of including analysis of sentiment within the atmosphere score within the CRM environment. The fact that sentiment scores are used together with a number of other useful parameters on the customer allows getting deeper insights, which enhances the management of customer relationships. As outlined by Medhat et al. [12] this improvement allows not only increasing the correctness of measuring customer sentiments but also provides opportunities for increasing engagement of customers even more. The continuing studies in this area are assumed to provide even more novel advancements in the field of CRM, making it more effective as well as efficient as per the customer‘s requirements.

III. Methodology

This section discusses how we assess customer sentiment and compute customer satisfaction scores. The introduction summarizes the first steps in managing multilingual customer feedback and describes the implementation of various sentiment analysis models. It also describes how the ensemble learning techniques were used to enhance sentiment classification performance. Moreover, it is highlighted that the results of sentiment analysis could used with other customer measures, via mathematical modeling tools, to generate a final satisfaction score. As shown in Figure 1,the system is initiated by first loading the appropriate NLP models and historical data for the purpose of assessing the system and then monitoring feedback in real-time. If feedback is available, it will be pre-processed and then analyzed for sentiment values. The sentiment results will be combined using ensemble methods, and finally, the key features and customer satisfaction score will be calculated.

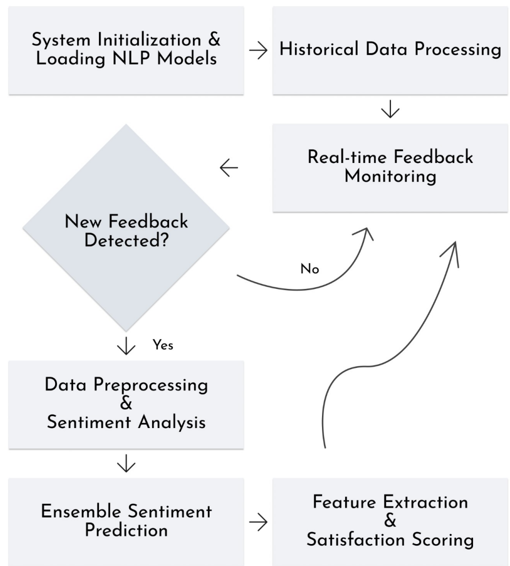

Figure 1. Overview of the Sentiment Analysis and Customer Satisfaction Scoring Process

A. Dataset

This research utilizes a dataset provided by the software company Next4Biz, comprising customer feedback from various technology firms collected through multiple communication channels. The data preprocessing phase involved removing special characters, transforming text to lower case, and stop word elimination so as to reduce bias in the analysis of sentiments. Temporal data were adjusted in terms of scale to facilitate efficient time series analysis and treatment of the temporal data in regard of missing data was done with all care to preserve data quality. Considering the feedbacks were given in different languages, Turkish texts were translated into English with the Translation models: Helsinki-NLP/opus-mt-tr-en model [7], which enabled the sentiment analysis on English models. This method guarantees that the efficiency scoring systems measuring the customer satisfaction level is universal and tenable as evaluation is done regardless of the language used. The main characteristics of the dataset used in the present research are presented in Table I.

Table I. STRUCTURED DATA SCHEMA FOR CUSTOMER FEEDBACK ANALYSIS AND SATISFACTION SCORING

No	Column	Description
1	Customer ID	A unique identifier systematically assigned to each customer.
2	Review Content	The narrative of feedback provided by clients, which encapsulates their perceptions and experiences.
3	Sentiment	Denotes the sentiment classification of the review, which may be categorized as positive, negative, or neutral.
4	Date of Review	The specific date on which each review was formally submitted by the customer.
5	Customer Registration Date	The first day of registration, the date when a customer starts using the system.
8	Last Activity Date	Date corresponding to customer's most recent interaction or engagement which can act as a measure for analyzing changes in customer behavior and interaction patterns over time.
6	Score	The most recently computed satisfaction score related to a client used in the current scoring refresh.

B. Model Selection and Ensemble Voting

In this research, we take an ensemble learning approach that emphasizes a versatile collection of sentiment analysis models, each model selected based on its strengths on differing text types. The ensemble learning approach employs deep learning models and established sentiment analysis tools to improve the accuracy and robustness of sentiment classification. Consider $M = \{m_1, m_2, \ldots, m_n\}$ represent the ensemble of models used in our system:

- m_1: `emre/turkish-sentiment-analysis` [13] — A model optimized for Turkish text, adept at capturing the language's unique nuances.
- m_2: `savasy/bert-base-turkish-sentiment-cased` [16] — A BERT-based model fine-tuned for sentiment analysis in Turkish.
- m_3:`cardiffnlp/twitter-roberta-base-sentiment` [1] — A RoBERTa model trained on Twitter data, effective for analyzing sentiment in informal English text.
- m_4: `VADER (Valence Aware Dictionary and Sentiment Reasoner)` [8] — A lexicon and rule-based tool, particularly effective for short texts and social media content.

The final sentiment classification for an input text x is determined by aggregating the predictions from each model in M. The sentiment prediction set $S(x)$ for an input x is defined as:

$$S(x) = \{s_i \mid s_i = m_i(x),\, m_i \in M\} \tag{1}$$

where s_i represents the sentiment prediction from model m_i. The ensemble voting mechanism calculates the number of votes $V(s)$ for each sentiment class s (e.g., positive, negative, neutral) as follows:

$$V(s) = \sum_{s_i \in S(x)} I(s_i = s) \tag{2}$$

In this study, $I(s_i = s)$ is the indicator function that equals 1 if s_i matches the sentiment class $s$otherwise it returns 0. Then we find the final sentiment Final_Sentiment(x) by checking which sentiment class has the highest vote count:

$$\text{Final\_Sentiment}(x) = \arg\max_s V(s) \tag{3}$$

This ensemble-based method collects multiple models and weaves out a single and more precise sentiment analysis which is effective and dependable regardless of the languages used and the forms of the texts.

C. Formulation of the Customer Satisfaction Score

In terms of Customer Relationship Management (CRM), having a solid and flexible customer satisfaction index is critical at ensuring retention and involvement of clients for a long duration. This part explains how to compute and dynamically adjust a new satisfaction score that combines among other dimensions, a basic score, customer activity, loyalty and feedback sentiment. The construct tested here is that it comprises the synthesis of a score that is created upon subsequent interaction with the customer.

1) Base Score Initializations: The Base Score (S_0) is the original or the initial score given to all customers when they register on the system. It is given a mid-point value of $S_0 = 50$, on which future modifications are based. The main objective of base scoring is equalizing the starting point for each customer irrespective of how each customer is being pursued or targeted by the initial assessment.This approach allows for equitable assessment, where any further score adjustments directly reflect the customer's specific behavior and engagement.

$$S_0 = 50 \tag{4}$$

2) Computation of the Activity Score: The Activity Score ($S_A(t)$) is dynamic in the sense that it captures the level of engagement of the customers towards the company over time. This score, which is reviewed on a monthly basis, modifies the base score depending on how long it has been since the last time the customer was engaged with the company (M_{last}):

$$S_A(t) = f(M_{\text{last}}) \tag{5}$$

Where $f(M_{\text{last}})$ is the function that is additionally defined for some time interval depending on the time since the last activity. These values are also given in detail in Table II showing the different grades of activity and how they affect the score. It relates the activity score designs to one of the given parameters, which is the frequency of interaction as an important measure of consumer acceptability or satisfaction with a service. So they have worked through the scoring system in such a way as to encourage activities and discourage non-activities.

Table II. ACTIVITY SCORE CALCULATION BASED ON TIME SINCE LAST ACTIVITY

Time Since Last Activity (M_{last})	**Activity Category**	**Activity Impact ($S_A(t)$)**
0-1 month	Extremely Active	$+2.5$
1-2 months	Very Active	$+2.0$
2-3 months	Active	$+1.5$
3-4 months	Moderately Active	$+0.5$
4-6 months	Slightly Inactive	-0.5
6-9 months	Mildly Inactive	-1.0
9-12 months	Inactive	-1.5
12-18 months	Very Inactive	-2.0
18-24 months	Long-term Inactive	-2.5
$>$ 24 months	Dormant	-3.0

The activity score $S_A(t)$ measures the level of natural interaction by the customer by appreciating the repeated interactions and condemning the dormancy of the customer. Within the positive adjustment especially within the last month, the customers who engage frequently stand to earn even a very high adjustment of $+2.5$ points. In a different category of scoring, those customers who have not interacted with the organization for a long time, say more than 24 months, are subjected to a penalty of -3.0 points. By utilizing this method, the customer satisfaction score is ensured to be a live score depicting the existing relationship of the customer and the corporation with all changes being reflected.

3) Loyalty Score Accrual Mechanism: The Loyalty Score ($S_L(t)$)) aims to recognize and reward duration of the relationship between the customer and the company. The customer will receive an increase of 0.25 points per month for the duration of their company engagement.As a result, the total relationship score will increase until after 15 years the relationship could yield a maximum of 30 points for loyalty.

$$S_L(t) = \min\left(t_{\text{reg}} \times 0.25, 30\right) \tag{6}$$

In this study, t_{reg} refers to the counting of months since the customer has registered.A period of 15 years was selected in this regard because it conforms to international best practices and ensures that the loyalty score demonstrates strong retention without becoming out of touch with long-term business goals.

4) Application of the Registration Bonus: The Registration Bonus (B_R) is a single bonus given exclusively to customers who have registered within three months. The Registration Bonus is equal to 10 points for customers, encouraging engagement sooner by incentivizing the relationship between that customer and the company to start off on a positive note.

$$B_R = \begin{cases} 10, & \text{if } t_{\text{reg}} \leq 3 \text{ months} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

5) Final Computation of the Customer Satisfaction Score: The overall Customer Satisfaction Score $S(t)$ is determined by aggregating the base score, activity score, loyalty score, and registration bonus. The final score is computed using the following equation:

$$S(t) = \min\left(\max\left(S_0 + S_A(t) + S_L(t) + B_R, S_{\text{min}}\right), S_{\text{max}}\right) \tag{8}$$

Where $S_{\text{min}} = 20$ establishes a limit, which by no customer's score let fall under this value. Where as, $S_{\text{max}} = 100$ keeps the score under this ceiling helping to maintain and balance the scoring system.

6) Mechanisms for Ongoing Score Adjustment: The customer satisfaction score is designed to be a dynamic measure, reflecting continuous interactions and feedback. The score is periodically updated through two key mechanisms:

a) Monthly Recalculation Based on Activity: The activity score is re-evaluated on a monthly basis to measure the customer's present engagement behavior. Updating the activity score on a monthly basis helps ensure the score remains indicative of the customer's ongoing relationship with the company, signifying the need for engagement to occur on a recurrent basis.

b) Integration of Sentiment Analysis from Feedback: After a response from the customer has been received, sentiment analysis is performed in order to evaluate whether the feedback is positive, neutral or negative. The score for customer satisfaction is then modified as follows.

$$S_{\text{feedback}} = S(t) + \Delta S_{\text{sentiment}} \tag{9}$$

Where $\Delta S_{\text{sentiment}}$ is determined as:

- Positive feedback: $\Delta S_{\text{sentiment}} = +5$ points
- Neutral feedback: $\Delta S_{\text{sentiment}} = 0$ points
- Negative feedback: $\Delta S_{\text{sentiment}} = -8$ points

This adjustment ensures that the score dynamically reflects the customer's emotional response, providing a more comprehensive measure of satisfaction. Figure 2 illustrates the customer satisfaction scoring process. The flowchart outlines both the initial score calculation and the monthly updates. Initially, the system starts with a default score, checks if the customer registered within three months for a registration bonus, and then calculates loyalty and activity scores. Monthly updates adjust these scores based on registration duration and recent interactions, with sentiment analysis adjusting the score according to feedback. The flowchart clarifies how each component contributes to an accurate and dynamic customer satisfaction score, promoting continued engagement and loyalty.

IV. EXPERIMENTAL RESULTS

In this part, the effectiveness of the customer satisfaction measurement tool is discussed, especially focusing on its ability to be adjusted dynamically according to the changing moods of the customers. The assessment of system performance allows estimating preliminary scores, making sentiment adjustments, and assessing customer interactions and loyalty every month. The results indicate that the system is efficient in accommodating any changes, such as in the mood of the customer in terms of the contentment levels so that the satisfaction level attributed towards each customer remains true at the present time.

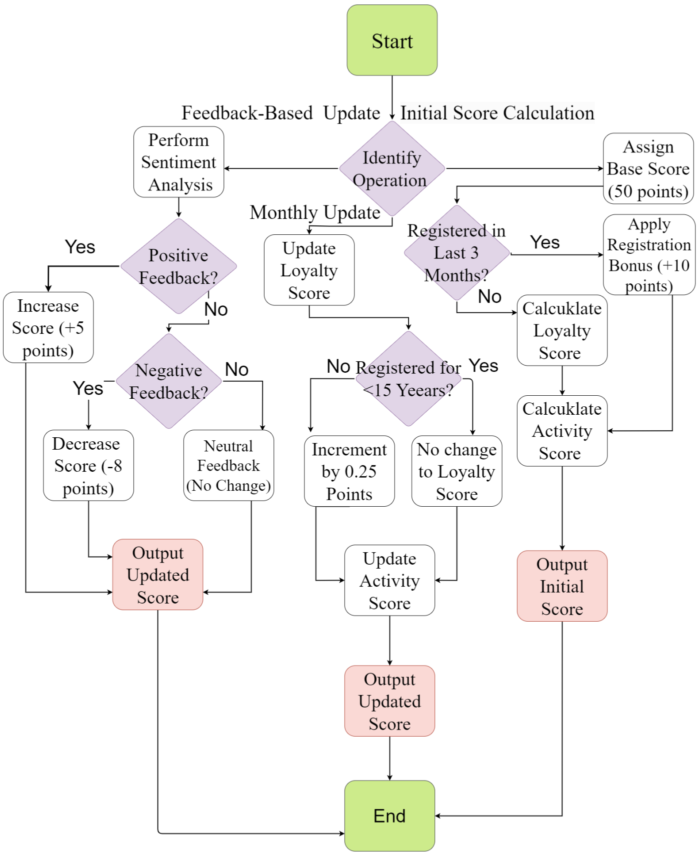

Figure 2. Flowchart of the Customer Satisfaction Scoring Process

1) Initial Score Calculations: The first score calculation is used for customer satisfaction evaluation especially where the base score, the loyalty and the activity levels are concerned. With this approach the system is able to separate the users into groups, such as those who are new users who are very loyal or those who have done more activities but are not that loyal.

Table III. Computation of Initial Scores for Varied Customer Profiles

Customer ID	5023	5276	6198	6748
Registration Date	2009-03-28	2015-01-01	2024-07-15	2017-05-10
Last Activity Date	2024-06-01	2024-08-20	2024-08-25	2024-07-30
Base Score	50	50	50	50
Loyalty Score	30.0	28.98	0.37	21.91
Activity Score	0.5	2.5	2.5	2.0
Registration Bonus	0	0	10	0
Initial Score	80.5	81.48	62.87	73.91

From Table III, it can be seen that the first score has many dimensions depending on the type of the customers. Customer 5023 was attributed a score of 80.5, which got the most weight due to a high loyalty score of 30.0. Even though the customer has had low activity recently, the loyalty score is vital to retaining a high overall score. Customer 5276 earned the highest score of 81.48, mainly due to strong loyalty and activity scores of 28.98 and 2.5, respectively. This is quite a fair score for the customer as it demonstrates substantial value from loyalty, coupled with growth in activity level. Customer 6198, having just registered, scored 62.87. It can be stated that the loyalty score is quite low at 0.37; however, the level of involvement and the addition of 10 points as a registration bonus increased the total score. Customer 6748 has a moderate score of 73.91, with reasonable brand loyalty and activity. This customer did not receive the customer registration bonus, suggesting that they had been with the company for a longer duration and remained moderately active.

2) Monthly Updates Based on Activity and Loyalty: Every month, customer scores are updated according to performance bars and loyalty increment, meaning that current scores will continue to change. The analysis is divided into two sections: Table IV contains a detailed profile of the customers, their past scores with the current date of their registration and last activity, whereas Table V gives an outline of the fresh scores as updated with recent activities and changes in loyalty. They, as a whole, demonstrate the enhanced process of the system in revising the customers' satisfaction scores whenever there are activities and or loyalty changes of the customers in the system.

Table IV. Customer Details and Previous Scores

Customer ID	Registration Date	Last Activity Date	Old Score
5023	2009-03-28	2024-06-01	85.5
5276	2015-01-01	2024-08-20	81.48
6198	2024-07-15	2024-08-25	62.87
6748	2017-05-10	2024-07-30	73.91

Table V. Updated Scores and Changes Based on Activity and Loyalty

Customer ID	Activity Bonus/Penalty	Loyalty Increase	New Score
5023	0.5	0.0	86.0
5276	2.5	0.26	84.24
6198	2.5	0.26	65.63
6748	2.0	0.26	76.17

Customer 5023 that has been inactive since June 2024 is also the last time he/she made note of in his/her activity logs – no transactions were recorded. The score then changed from 85.5 to 86.0 which was caused by an activity bonus of 0.5 points. Since this customer surpassed the 15-year loyalty duration no additional loyalty reward was awarded as the customer was inactive recently but many years of loyalty were valued.Customer 5276 has been displaying improvement, turning 81.48 into 84.24. There was also a 2.5 points activity bonus which was attributed to the growth plus 0.26 loyalty growth contributing towards a total increase of 2.76 in the score.Customer 6198 who from the activity grew has watched their scores change from 62.87 to 65.63 at the close of the period 2.5 being from activity and 0.26 from loyalty. This illustrates the plan of the system to support new clients in becoming effective at the beginning. Scoring of Customer 6748 went from 73.91 to a bold 76.17 thanks to 2.0 activity bonus points accumulated and 0.26 loyalty points earned. Total score has increased by 2.26 illustrating how the new activity together with loyalty is promoted by the system.

3) Feedback-Driven Score Adjustments: Customer feedback is very important in the real-time variation of customer satisfaction score. The system incorporates several types of feedback such as positive, neutral and negative in changing a customer's score. Specifically, positive feedback increases the score under consideration, neutral feedback retains the score as it is, and negative feedback leads to a decrease in score. In this way, evaluation and metrics of customer satisfactions are accurate at any time and are in synchronism with the interactions aimed at achieving customer satisfaction.

Table VI. CUSTOMER 5023: FEEDBACK AND SCORING DETAILS

Customer ID	5023
Previous Score	86.0
New Score	91.0
Sentiment	Positive
Sentiment Affect	+5
Feedback	Happy with my new laptop. The staff was helpful, the price was good, and delivery was quick. They replaced a faulty charger without any issues. I'll shop here again.

Table VII. CUSTOMER 6198: FEEDBACK AND SCORING DETAILS

Customer ID	6198
Previous Score	65.63
New Score	57.63
Sentiment	Negative
Sentiment Affect	-8
Feedback	I'm very disappointed with my new phone; the battery lasts only a few hours, far from what was promised. The store staff were unhelpful, pushing accessories instead of solving the problem. I feel ripped off, and returning it seems like a hassle given their poor customer service. I wouldn't recommend this product or company to anyone.

As seen in Tables VI and VII, the feedback-driven score adjustments effectively reflect how customer feedback impacts overall satisfaction. Customer 5023 provided a number of positive remarks that resulted in the satisfaction score increasing from 86.0 to 91.0. This increase indicates that the system was accurate in identifying a positive customer experience and raising the customer feedback score.Customer 6198 was dissatisfied, and the customer's satisfaction score fell significantly from 65.63 to 57.63 due to negative feedback. The significant reduction in score highlights the system's focus on addressing serious customer complaints promptly. Serious complaints that go unaddressed can damage overall customer satisfaction and confidence in the company.

V. CONCLUSION

This paper presented an advanced customer satisfaction scoring model which incorporates advanced sentiment analysis techniques and dynamic scoring methods particular to a CRM system. With the integration of the latest transformer architectures into an ensemble learning model, namely, BERT and RoBERTa, the proposed system guarantees a high degree of accuracy in sentiment analysis. Additionally, the combination of these findings with other parameters, such as loyalty and engagement evaluation, provides the system with an accurate and flexible performance assessment of customer satisfaction, which is capable of changing in the course of continuous customer interaction. The results gained in this research show that the system is able to modify customer satisfaction scores and does it in real-time accounting for both temporary and permanent customer characteristics. Such a feature is important in modern business settings where customer attitudes and expectations are subject to change within a short period of time.In addition, the ability of the system to be adapted for Turkish language processing content proves its suitability and applicability in Turkish markets and it serves as a powerful tool for the firms operating in such markets.In conclusion, this project offers a significant contribution to the area of CRM given its provision of a system that is both expandable and adaptable, while at the same time providing accurate information on customer satisfaction. Thanks to the incorporation of the latest sentiment analysis technology with the capability of altering real-time scores on the fly, businesses remain fully informed about their customers at all times. This paves the way for formulating strategies that promote maximum engagement and retention of customers. In the subsequent research, the main emphasis will be on the widening of the boundary for this system to be scalable in different industries as well as on utilizing this system to enable further enhancements that will enhance accuracy and efficiency in anticipating client needs and actions.

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