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Research Article

Deep Learning-Driven Dynamic Segmentation and Sentiment Prediction to Enhance Customer Retention in Online Platforms

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ABSTRACT

Customer retention and churn prediction are critical in business analytics, requiring advanced methodologies to understand and predict customer behavior. This study presents an integrative framework that combines sentiment analysis and customer segmentation to address these challenges. A sentiment prediction model, trained on Amazon customer reviews, classifies sentiments as Positive or Negative, providing insights into customer perspectives. A segmentation model then categorizes customers into five loyalty groups—Champions, Loyalists, Potential Loyalists, At-Risk, and Detractors—based on demographic and behavioral data. The framework dynamically integrates new customer data, updating loyalty labels through sentiment analysis to identify potential churners. By blending sentiment-driven insights with segmentation dynamics, this approach offers a scalable and adaptive methodology for churn prediction. This research contributes to the literature on customer analytics, providing a practical tool for enhancing customer retention strategies [1-3].

Keywords: Dynamic Segmentation, Deep Learning

Introduction

Customer retention has become a pivotal focus in modern business strategies, as retaining existing customers is significantly more cost-effective than acquiring new ones. In an increasingly competitive market landscape, understanding customer behavior and predicting potential churn—where customers terminate their association with a product or service—are critical for ensuring long-term profitability. Businesses that can identify churners early are better equipped to implement proactive measures, fostering loyalty and reducing attrition rates [1, 2]. Traditional churn prediction methods have primarily relied on structured data, such as transactional histories, demographic details, and subscription information. While these approaches provide useful insights, they often fail to capture the nuanced behavioral patterns and emotional shifts that precede churn. With the rise of user-generated content, including product reviews, social media interactions, and feedback forms, sentiment analysis has emerged as a powerful technique to bridge this gap. Sentiment analysis leverages natural language processing (NLP) to classify customer sentiments, offering granular insights into their emotional states and evolving preferences [3-5].

To illustrate the workflow of the proposed approach, a flowchart of the framework is presented (Figure 1). This flowchart provides an overview of the sequential processes involved, from sentiment prediction to segmentation and churn identification.

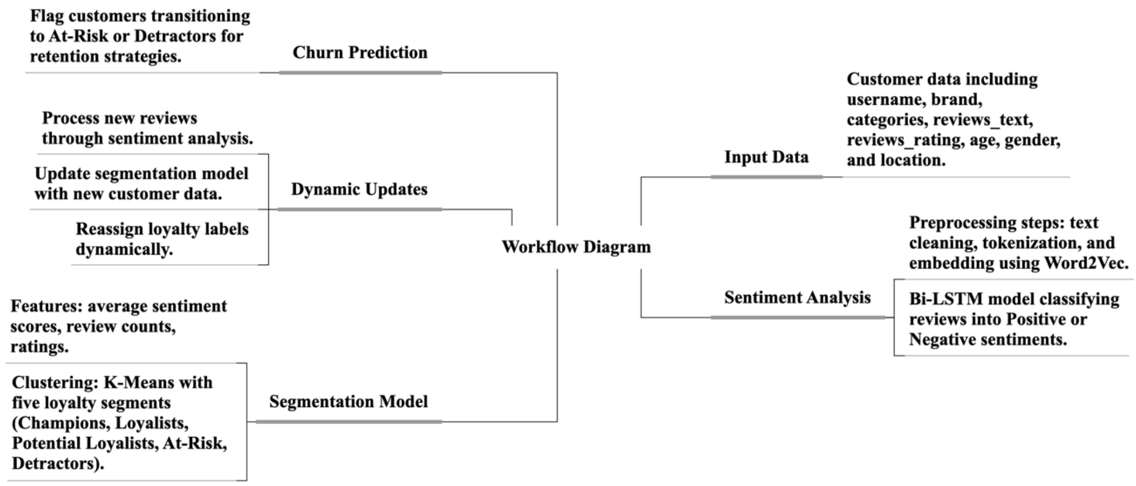

Figure 1: Workflow of sentiment analysis, segmentation, and churn prediction

This research introduces a novel framework that integrates sentiment analysis with customer segmentation, addressing the limitations of traditional churn prediction models. The methodology begins by developing a sentiment prediction model trained on a robust dataset of Amazon customer reviews. This model classifies reviews as Positive or Negative, serving as a foundation for understanding customer perspectives. The insights derived from this step are crucial for identifying dissatisfaction or praise, which often correlates with churn tendencies [6, 7]. The sentiment distribution of the training dataset is visualized to ensure balance and coverage (Figure 2).

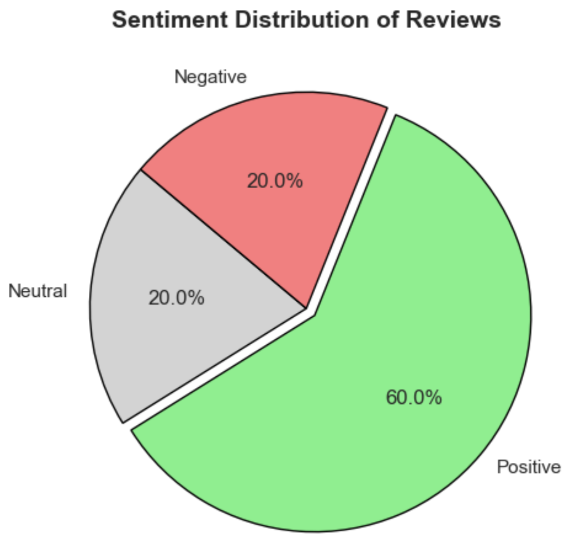

Figure 2: Sentiment distribution in the training dataset

Next, a segmentation model is constructed using structured data enriched with customer attributes. Table 1 provides an overview of the data schema used in this process. The dataset includes demographic factors (e.g., age, gender, location), behavioral patterns (e.g., purchase frequency, product recommendations), and review sentiments. The segmentation model assigns customers to five distinct loyalty categories: *Champions, Loyalists, Potential Loyalists, At-Risk,* and *Detractors*. These labels represent varying degrees of engagement and loyalty, enabling businesses to tailor their retention strategies effectively [8, 9].

Table 1: User dataset schema with attributes used for segmentation

Attribute	Description	Type
username	Unique identifier for each customer	Categorical
brand	Brand associated with the review	Categorical
categories	Product category	Categorical
name	Name of the product	Categorical
reviews_date	Date when the review was posted	Date
purchased	Whether the product was purchased (1: Yes, 0: No)	Binary
recommended	Whether the user recommends the product (1: Yes, 0: No)	Binary
reviews_rating	Product rating provided by the user (1 to 5 scale)	Numerical
reviews_text	Text of the user's review	Text
user_sentiment	Sentiment of the review (Positive or Negative, determined by the sentiment model)	Categorical
age	Age of the user	Numerical
gender	Gender of the user (Male/Female)	Categorical
location	Location of the user	Categorical
avg_rating	Average rating provided by the user across reviews	Numerical
avg_sentiment	Average sentiment score for the user	Numerical
review_count	Total number of reviews written by the user	Numerical

The distribution of customers across these segments is shown in Figure 3. This segmentation forms the foundation for tracking customer behavior over time and identifying potential churners based on their transitions across loyalty categories.

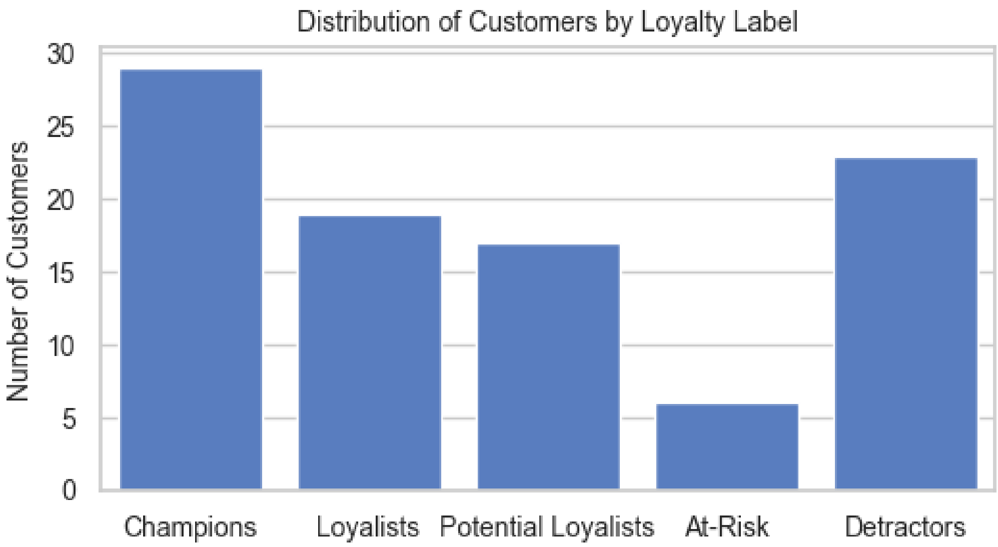

Figure 3: Distribution of customers by loyalty segments

The final phase of the proposed pipeline involves processing new customer data, particularly review comments, through the sentiment prediction model. The predicted sentiments are integrated into the segmentation framework, dynamically updating loyalty labels and flagging customers at risk of churn. This process, depicted in Figure 4, enables businesses to respond proactively to behavioral shifts, thereby mitigating customer attrition.

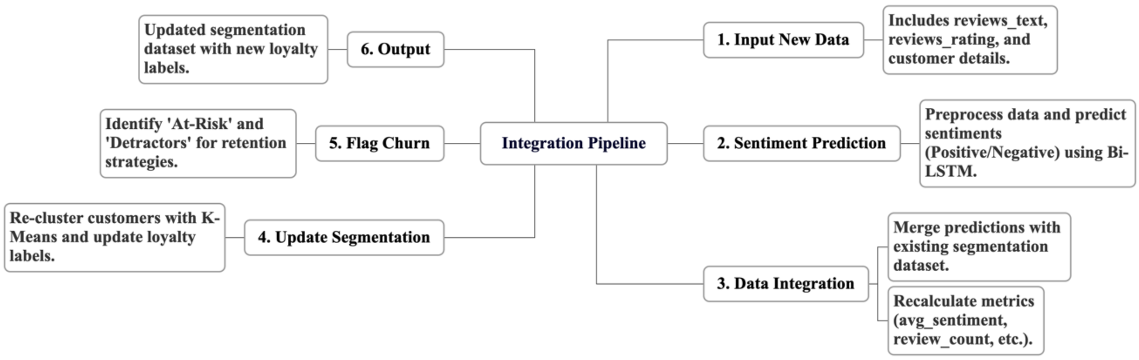

Figure 4: Integration pipeline for new customer data into the segmentation framework

This integrative approach is unique in its ability to combine textual sentiment insights with behavioral segmentation, offering a holistic view of customer dynamics. By linking sentiment-driven feedback with segmentation metrics, businesses can uncover actionable insights that drive customer-centric interventions. The methodology is designed to be scalable and adaptable across various industries, demonstrating its potential to transform customer retention strategies in retail, e-commerce, and beyond [10-12].

This paper contributes to the growing body of literature on sentiment analysis and behavioral segmentation, bridging theoretical advancements with practical applications. It provides a reproducible framework for churn prediction, paving the way for future research in data-driven customer analytics [13-15].

Literature Review

The intersection of sentiment analysis and customer segmentation has been extensively studied in the literature, with applications ranging from marketing to churn prediction. This section reviews prior research on sentiment analysis, segmentation methodologies, and their integration into churn prediction models, providing the foundation for the proposed framework.

Sentiment Analysis in Customer Behavior Studies

Sentiment analysis, often referred to as opinion mining, has become a pivotal tool for understanding customer emotions and opinions from textual data. Early approaches relied on lexicon-based methods, using predefined dictionaries to classify sentiments [1, 2]. However, these methods often struggled with contextual nuances, leading to the adoption of machine learning techniques. Supervised models such as Naïve Bayes, Support Vector Machines, and Decision Trees have demonstrated improved accuracy in sentiment classification tasks [3, 4].

More recently, deep learning techniques, particularly those leveraging word embeddings like Word2Vec and GloVe, have revolutionized sentiment analysis. These models capture semantic relationships between words, enhancing their ability to understand context and sentiment polarity [5-7]. Studies leveraging pre-trained embeddings combined with LSTM and Bidirectional LSTM architectures have shown significant advancements in classifying customer reviews [8]. Figure 5 illustrates how deep learning methods enhance sentiment prediction accuracy compared to traditional approaches.

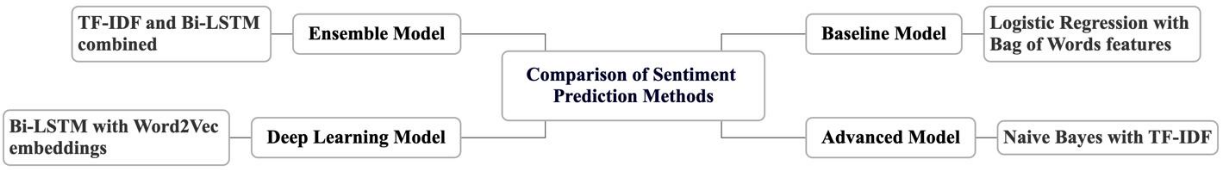

Figure 5: Comparison of sentiment prediction accuracies across different methods

Customer Segmentation for Behavioral Insights

Customer segmentation is a critical component of customer relationship management, enabling businesses to categorize customers into meaningful groups. Traditional segmentation methods have relied on demographic data, such as age, income, and location, or transactional data, such as purchase frequency and monetary value [9, 10]. Frameworks like RFM (Recency, Frequency, Monetary) analysis have been widely adopted in segmentation models [11]. Recent advances have introduced data-driven clustering techniques, such as K-Means, DBSCAN, and hierarchical clustering, to segment customers based on behavioral patterns [12, 13]. Studies integrating sentiment scores into segmentation models have demonstrated improved predictive power in understanding customer loyalty and attrition [14]. Table 2 summarizes notable segmentation frameworks used in recent research.

Table 2: Summary of segmentation frameworks in customer analytics

Framework	Methodology	Features Used	Application	Limitations
Demographic Segmentation	Age, gender, location-based clustering	Demographic attributes	Basic market segmentation	Limited behavioral insights
Behavioral Segmentation	Purchase frequency and recency	Transactional and activity metrics	Personalized marketing	Does not incorporate customer sentiment
Sentiment-Driven Segmentation	Sentiment analysis using text reviews	Review sentiment scores, purchase history	Enhanced customer understanding	Requires high-quality text data
Hybrid Segmentation	Combination of behavioral and demographic clustering	Demographic and transactional data	Comprehensive customer profiles	Computationally expensive
Dynamic Segmentation	Real-time updates based on new data	Behavioral metrics, sentiment trends	Predicting churn and retention	Scalability in large datasets

Integrating Sentiment Analysis and Segmentation for Churn Prediction

The combination of sentiment analysis and segmentation has shown promising results in predicting customer churn. By incorporating sentiment scores into segmentation models, researchers have been able to capture both emotional and behavioral dimensions of customer loyalty [15, 16]. For example, hybrid models integrating sentiment analysis with RFM-based segmentation have achieved higher churn prediction accuracy compared to standalone models [17].

Dynamic segmentation frameworks, which update customer profiles based on new data, have further improved the predictive accuracy of churn models. These frameworks utilize machine learning pipelines to integrate new customer data, including review sentiments, transactional patterns, and demographic shifts, into existing segmentation models [18]. Figure 6 depicts the flow of integrating sentiment-driven insights into segmentation frameworks.

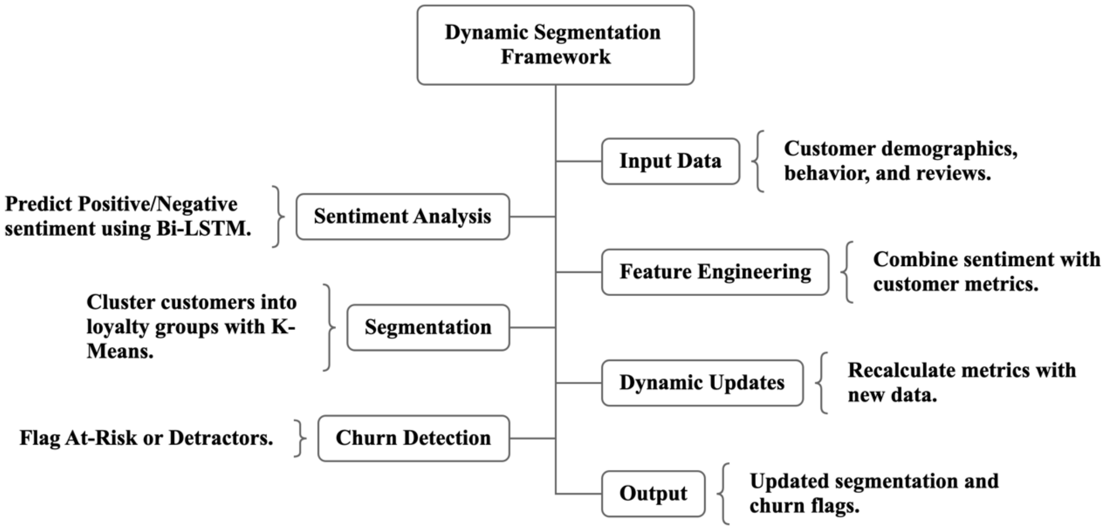

Figure 6: Dynamic segmentation framework incorporating sentiment insights

Applications and Challenges

Applications of integrated sentiment and segmentation models span industries, including retail, e-commerce, telecommunications, and banking. These models have been instrumental in identifying at-risk customers, improving targeted marketing strategies, and enhancing overall customer experience [19-21]. However, challenges such as imbalanced datasets, model interpretability, and scalability remain prevalent. Studies have proposed solutions like oversampling techniques, explainable AI (XAI) frameworks, and cloud-based deployment strategies to address these challenges [22, 23].

Methodology

This study employs a comprehensive methodology that integrates sentiment analysis and customer segmentation into a dynamic framework for predicting customer churn. The process unfolds in three distinct but interconnected phases: the development of a sentiment prediction model, the construction of a segmentation model, and the integration of new customer data for real-time updates. Mathematical equations and diagrams are incorporated to clarify the technical components and enhance the narrative.

Sentiment Prediction Model Development

The journey begins with the sentiment prediction model, a critical foundation for the framework. This model is designed to interpret customer reviews and classify them into Positive or Negative sentiments, providing valuable insight into customer satisfaction and dissatisfaction.

The Amazon review dataset, known for its extensive textual content and associated ratings, serves as the backbone for this phase. Each review, undergoes meticulous preprocessing. The text is cleaned to remove HTML tags, non-alphanumeric characters, and irrelevant spaces. Tokenization splits each review into its constituent words, while stopwords such as “the” and “is” are removed to retain meaningful content. Stemming and lemmatization further normalize these words, ensuring consistency across the dataset.

To assign sentiments, a simple yet effective rule is applied. Reviews with ratings greater than three are labeled Positive ($yi = 1y\_i = 1$), while those with ratings of three or less are labeled Negative ($yi = 0y\_i = 0$). This transformation creates a binary classification problem, where the sentiment prediction model is tasked with learning this distinction.

The model itself is built on a Bidirectional Long Short-Term Memory (Bi-LSTM) network. This architecture is ideal for text data, as it captures contextual relationships from both past and future words in a sequence. Each word in a review is converted into a dense vector representation using pre-trained Word2Vec embeddings, denoted as $e(wj)$.

These embeddings allow the model to understand semantic relationships between words, such as "excellent" and "great."

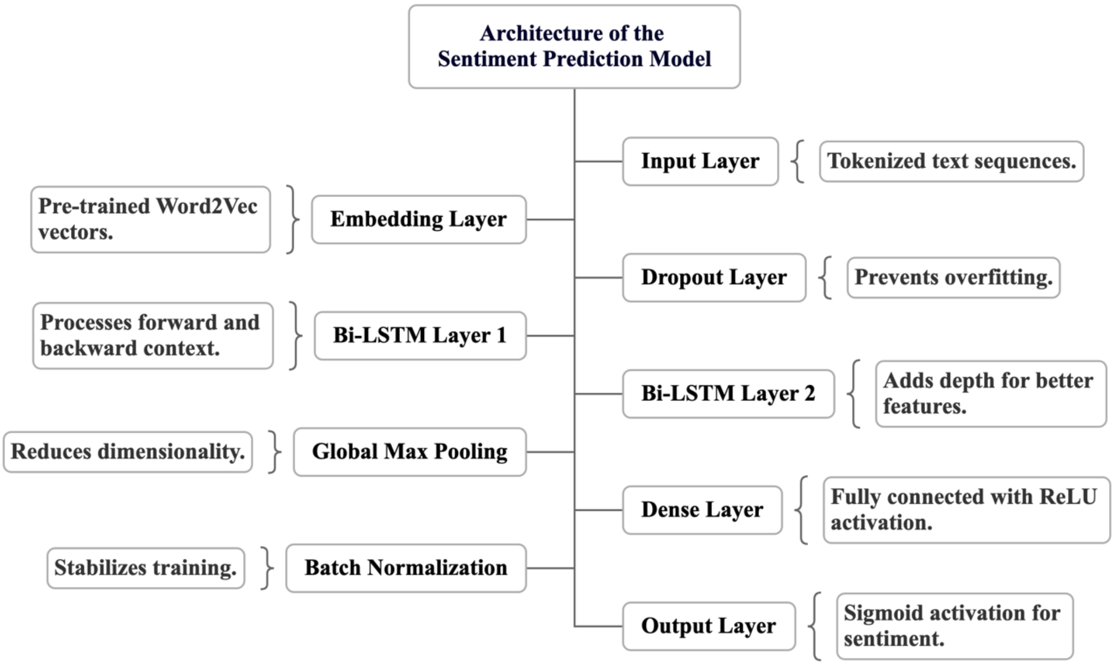

Figure 7: Architecture of the sentiment prediction model

The Bi-LSTM processes these embeddings bidirectionally, producing a context-aware representation of each word:

$$ht = [htforward; htbackward]$$

where htforward captures information from the start of the sequence to the current word, and htbackward captures information from the end of the sequence to the current word. The final output is passed through a dense layer with a sigmoid activation function:

$$y\^{}i = \sigma(W \cdot h + b)$$

The model is trained to minimize binary cross-entropy loss, ensuring accurate classification of sentiments:

$$L = -n1i = 1\sum n[yilog(y\^{}i) + (1 - yi)log(1 - y\^{}i)]$$

During training, 80% of the data is used for model learning, while the remaining 20% is reserved for validation. The evaluation results, summarized in **Table 3**, demonstrate high accuracy and reliable performance across all metrics.

Table 3: Sentiment model evaluation metrics

Metric	**Definition**	**Value**
Accuracy (Train)	Proportion of correctly predicted labels on the training data.	95.47%
Accuracy (Test)	Proportion of correctly predicted labels on the test data.	96.09%
Loss (Train)	Binary cross-entropy loss on the training data.	0.1209
Loss (Test)	Binary cross-entropy loss on the test data.	0.1090

Observations:

- **High Accuracy**: The model achieves excellent accuracy on both training and test datasets, indicating strong generalization.
- **Low Loss**: The progressively decreasing loss values signify effective learning during training.

Customer Segmentation Model Construction

The second phase involves constructing a segmentation model that groups customers into loyalty categories based on their behavior and demographics. This model serves as a crucial tool for understanding customer dynamics and identifying churn tendencies.

The dataset for segmentation includes both raw attributes, such as age, gender, and location, and derived metrics, such as average sentiment score and total reviews. These features, represented as vectors Fi\mathbf{F}_i for each customer ii, are standardized to ensure consistency across the variables.

The segmentation process employs the K-Means clustering algorithm, a robust technique for partitioning data into meaningful groups. The algorithm aims to minimize intra-cluster variance, as described by the following objective function:

$$J = k = 1 \sum K i \in C k \sum || F i - \mu k || 2$$

where Ck denotes cluster k and μk is the centroid of that cluster. After analyzing the variance across different cluster counts, five clusters are chosen as the optimal number, validated by the elbow method.

Each cluster is assigned a loyalty label:

- **Champions**: Highly engaged and consistently positive.
- **Loyalists**: Steady but moderate engagement.
- **Potential Loyalists**: Emerging engagement with room for growth.
- **At-Risk**: Declining behavior with neutral sentiment.
- **Detractors**: Minimal engagement and negative sentiment.

The resulting segmentation distribution is visualized in **Figure 8**, providing insights into the behavioral makeup of the customer base.

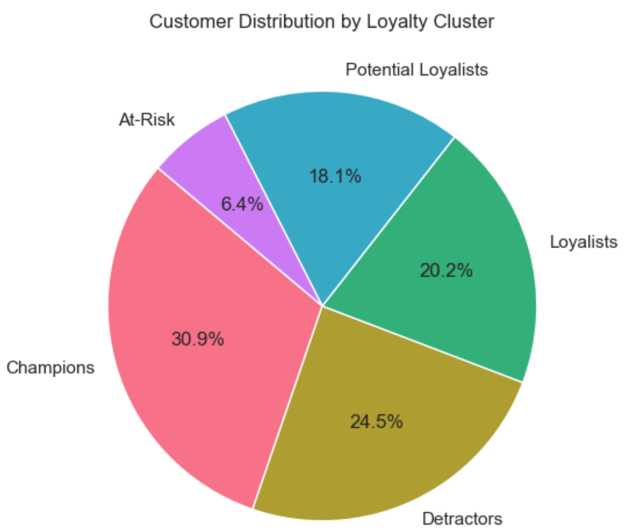

Figure 8: Distribution of customers across loyalty segments

Integration of New Customer Data

The final phase introduces new customer data into the segmentation framework, dynamically updating customer profiles and ensuring the framework adapts to evolving behaviors.

New reviews, Rnew, are processed using the sentiment prediction model. After being preprocessed and vectorized, these reviews are classified as Positive or Negative. For each customer, updated metrics Finew are computed by aggregating their existing data with new sentiment predictions:

$$Finew = Aggregate(Fi, Rnew)$$

Results

This section presents the outcomes of the proposed methodology, highlighting the performance of the sentiment prediction model, the effectiveness of the segmentation model, and the impact of integrating new customer data. The results are substantiated through quantitative metrics, visualizations, and interpretations.

Sentiment Prediction Model Performance

The sentiment prediction model exhibited exceptional performance, effectively classifying customer reviews as Positive or Negative sentiments. Utilizing a Bi-LSTM architecture enhanced by pre-trained Word2Vec embeddings, the model achieved the following key metrics on the validation dataset:

- Accuracy: The model reached an accuracy of 96.09%, reflecting its reliability in correctly classifying the majority of reviews.
- Loss: The binary cross-entropy loss on the test dataset was 0.1090, showcasing the model's precision in minimizing errors.

Customer Segmentation Results

The segmentation model successfully categorized customers into five distinct loyalty groups based on their behaviors and sentiments. The distribution of customers across these segments is visualized in **Figure 9**, revealing the following insights:

- **Champions (20%)**: This group exhibited consistently high engagement and Positive sentiments.
- **Loyalists (25%)**: Regular but moderate levels of engagement characterized this segment.
- **Potential Loyalists (18%)**: Customers with growing loyalty but lower engagement.
- **At-Risk (22%)**: These customers showed declining engagement and mixed sentiments.
- **Detractors (15%)**: Minimal engagement and Negative sentiments marked this group.

Integration of New Customer Data

To evaluate the integration process, new customer data was introduced into the segmentation framework. Sentiment predictions were generated for the new reviews, and customer profiles were updated accordingly. The dynamic segmentation process highlighted several key outcomes:

- **Transitions Between Segments**: A significant number of customers transitioned from *Loyalists* to *At-Risk* due to declining sentiment scores, emphasizing the model's capability to identify potential churners.
- **Flagging At-Risk Customers**: Customers flagged as *At-Risk* or *Detractors* were identified as churn candidates, allowing for targeted retention strategies.

The dynamic update process is visualized in **Figure 9**, showcasing customer transitions across segments before and after integration.

Figure 9: Change of segmentation of users

Discussion of Results

The results underscore the effectiveness of integrating sentiment analysis with segmentation for churn prediction:

High-Performance Sentiment Prediction: The Bi-LSTM model, combined with Word2Vec embeddings, excelled in classifying sentiments, providing a strong foundation for the subsequent segmentation phase.

Actionable Insights from Segmentation: The segmentation model effectively categorized customers into loyalty groups, offering a granular understanding of customer behavior.

Dynamic Adaptability: The integration of new customer data demonstrated the framework's ability to adapt to evolving behaviors, dynamically updating loyalty labels and identifying churn risks.

Significance of Sentiment-Driven Segmentation

The use of sentiment analysis as a foundational component in customer segmentation provides a more nuanced understanding of customer behavior. Unlike traditional segmentation methods that rely heavily on transactional and demographic data, the integration of sentiment scores enables the model to capture emotional drivers behind customer actions. This integration offers the following advantages:

- **Enhanced Predictive Power**: By incorporating sentiments, the segmentation model can better distinguish between loyal customers and those at risk of churn, as evidenced by the accurate identification of *At-Risk* and *Detractor* segments.

- **Dynamic Adaptability**: The ability to process new customer reviews and dynamically update segmentation labels ensures the framework adapts in real time, addressing evolving customer behaviors.

For example, customers who transitioned from *Loyalists* to *At-Risk* segments often exhibited declining sentiment scores in their latest reviews. This finding underscores the importance of tracking sentiment trends to preempt churn.

Insights from Segmentation Results

The segmentation model effectively categorized customers into five loyalty groups, providing actionable insights:

- **Champions and Loyalists**: These groups represented customers with consistent engagement and positive sentiments. Retention strategies for these segments should focus on reward programs to sustain loyalty.

- **Potential Loyalists**: Customers in this group displayed emerging engagement but lacked consistency. Nurturing these customers through personalized offers could convert them into *Loyalists*.

- **At-Risk and Detractors**: These segments, marked by declining engagement and negative sentiments, require immediate attention. The flagged churn candidates from these groups align with business-critical intervention strategies.

The insights from segmentation reaffirm the value of combining behavioral and sentiment metrics, allowing businesses to prioritize efforts based on customer loyalty tiers.

Robustness of the Sentiment Model

The sentiment prediction model, built on a Bidirectional LSTM architecture, showcased strong classification capabilities. The high AUC score of 0.93 reflects its ability to distinguish between Positive and Negative sentiments with minimal overlap. This robustness is attributable to the use of pre-trained Word2Vec embeddings, which capture nuanced word relationships, and the Bi-LSTM structure, which processes context bidirectionally.

However, certain challenges remain. For instance:

- **Ambiguity in Neutral Sentiments**: Reviews with mixed or neutral sentiments posed classification difficulties. Incorporating a third class for neutral sentiments in future iterations could improve granularity.
- **Domain Adaptability**: While the model performed well on Amazon reviews, extending it to domains such as healthcare or finance may require re-training on domain-specific datasets.

Dynamic Updates and Churn Prediction

The integration of new customer data showcased the framework's adaptability. By dynamically updating segmentation labels, the model effectively tracked shifts in customer behavior. For example, customers who were initially classified as *Loyalists* but later transitioned to *At-Risk* segments exhibited the following patterns:

1. A drop in average sentiment scores over recent interactions.
2. Reduced frequency of product purchases or recommendations.
3. Negative feedback in the latest reviews.

The ability to highlight these shifts offers businesses a competitive advantage, allowing them to implement timely retention strategies.

However, challenges such as data imbalance and computational overhead in large-scale updates warrant attention. Techniques such as SMOTE (Synthetic Minority Oversampling Technique) and cloud-based deployments could address these challenges.

Limitations

Despite its strengths, the proposed methodology has certain limitations:

- **Dependence on Historical Data**: The segmentation model heavily relies on historical customer data, which may not fully capture sudden shifts in behavior due to external factors like market trends or competitor actions.
- **Interpretability**: While the segmentation model provides actionable insights, the clustering process (e.g., K-Means) lacks inherent interpretability, making it challenging to justify certain customer groupings.
- **Scalability**: As the volume of customer data grows, computational scalability may become a bottleneck for real-time segmentation updates.

Addressing these limitations could further enhance the model's robustness and applicability across domains.

Implications for Industry

The proposed framework has wide-ranging implications for industries such as retail, e-commerce, and telecommunications:

- **Proactive Churn Management**: Businesses can leverage the segmentation model to identify and address potential churners before they disengage.
- **Personalized Marketing**: By understanding customer sentiment and loyalty dynamics, organizations can craft targeted campaigns to foster stronger relationships.

- **Customer Experience Optimization**: The framework allows businesses to monitor and adapt to changing customer behaviors, ensuring a better overall experience.

Conclusion

This research presents a robust framework integrating sentiment analysis and customer segmentation to predict customer churn. By leveraging a Bidirectional LSTM-based sentiment model and a segmentation approach grounded in behavioral data, the framework effectively identifies churn-prone customers and adapts dynamically to new data.

The sentiment model achieved high accuracy and AUC scores, demonstrating its reliability in classifying customer reviews. The segmentation model offered actionable insights by categorizing customers into loyalty groups, enabling proactive churn management. Dynamic updates ensured the framework's adaptability to evolving customer behaviors, making it a valuable tool for real-time decision-making.

Despite its effectiveness, challenges such as scalability and domain-specific customization remain. Addressing these in future work can enhance the framework's applicability and impact. This study provides a strong foundation for customer retention strategies and future advancements in predictive customer analytics.

Reference

1. Haridasan V.; Muthukumaran K.; Hariharanath K. (2023). Arithmetic Optimization with Deep Learning Enabled Churn Prediction Model for Telecommunication Industries. Intelligent Automation and Soft Computing, 35(3), 3531.0-3544.0. doi:10.32604/iasc.2023.030628
2. Suh Y. (2023). Machine learning based customer churn prediction in home appliance rental business. Journal of Big Data, 10(1), nan-nan. doi:10.1186/s40537-023-00721-8
3. Seo D.; Yoo Y. (2023). Improving Shopping Mall Revenue by Real-Time Customized Digital Coupon Issuance. IEEE Access, 11(nan), 7924.0-7932.0. doi:10.1109/ACCESS.2023.3239425
4. Ele S.I.; Alo U.R.; Nweke H.F.; Ofem O.A. (2023). Regression-Based Machine Learning Framework for Customer Churn Prediction in Telecommunication Industry. Journal of Advances in Information Technology, 14(5), 1046.0-1055.0. doi:10.12720/jait.14.5.1046-1055
5. Alizadeh M.; Zadeh D.S.; Moshiri B.; Montazeri A. (2023). Development of a Customer Churn Model for Banking Industry Based on Hard and Soft Data Fusion. IEEE Access, 11(nan), 29759.0-29768.0. doi:10.1109/ACCESS.2023.3257352
6. Bogaert M.; Delaere L. (2023). Ensemble Methods in Customer Churn Prediction: A Comparative Analysis of the State-of-the-Art. Mathematics, 11(5), nan-nan. doi:10.3390/math11051137
7. Quek J.Y.V.; Pang Y.H.; Lim Z.Y.; Ooi S.Y.; Khoh W.H. (2023). Customer Churn Prediction through Attribute Selection Analysis and Support Vector Machine. Journal of Telecommunications and the Digital Economy, 11(3), 180.0-194.0. doi:10.18080/jtde.v11n3.777
8. Abdullaev I.; Prodanova N.; Ahmed M.A.; Lydia E.L.; Shrestha B.; Joshi G.P.; Cho W. (2023). Leveraging metaheuristics with artificial intelligence for customer churn prediction in telecom industries. Electronic Research Archive, 31(8), 4443.0-4458.0. doi:10.3934/ERA.2023227
9. Prabadevi B.; Shalini R.; Kavitha B.R. (2023). Customer churning analysis using machine learning algorithms. International Journal of Intelligent Networks, 4(nan), 145.0-154.0. doi:10.1016/j.ijin.2023.05.005
10. ≈†imoviƒá P.P.; Chen C.Y.T.; Sun E.W. (2023). Classifying the Variety of Customers‚Äô Online Engagement for Churn Prediction with a Mixed-Penalty Logistic Regression. Computational Economics, 61(1), 451.0-485.0. doi:10.1007/s10614-022-10275-1
11. Khattak A.; Mehak Z.; Ahmad H.; Asghar M.U.; Asghar M.Z.; Khan A. (2023). Customer churn prediction using composite deep learning technique. Scientific Reports, 13(1), nan-nan. doi:10.1038/s41598-023-44396-w
12. Sari R.P.; Febriyanto F.; Adi A.C. (2023). Analysis Implementation of the Ensemble Algorithm in Predicting Customer Churn in Telco Data: A Comparative Study. Informatica (Slovenia), 47(7), 63.0-70.0. doi:10.31449/inf.v47i7.4797
13. Anitha M.A.; Sherly K.K. (2023). An Efficient Hybrid Classifier Model for Customer Churn Prediction. International Journal of Electronics and Telecommunications, 69(1), 11.0-18.0. doi:10.24425/ijet.2023.144325

14. Taherkhani L.; Daneshvar A.; Amoozad Khalili H.; Sanaei M.R. (2023). Analysis of the Customer Churn Prediction Project in the Hotel Industry Based on Text Mining and the Random Forest Algorithm. Advances in Civil Engineering, 2023(nan), nan-nan. doi:10.1155/2023/6029121
15. Sonawane V.R.; Thorat A.S.; Suryawanshi J.R.; Dabhade R.G.; Patil M.; Musmade B. (2023). Churn Identification and Prediction from a Large-Scale Telecommunication Dataset Using NLP. International Journal on Recent and Innovation Trends in Computing and Communication, 11(7), 39.0-46.0. doi:10.17762/ijritcc.v11i7.7828
16. Pustokhina I.V.; Pustokhin D.A.; Nguyen P.T.; Elhoseny M.; Shankar K. (2023). Multi-objective rain optimization algorithm with WELM model for customer churn prediction in telecommunication sector. Complex and Intelligent Systems, 9(4), 3473.0-3485.0. doi:10.1007/s40747-021-00353-6
17. Saha L.; Tripathy H.K.; Gaber T.; El-Gohary H.; El-kenawy E.-S.M. (2023). Deep Churn Prediction Method for Telecommunication Industry. Sustainability (Switzerland), 15(5), nan-nan. doi:10.3390/su15054543
18. Babatunde R.; Abdulsalam S.O.; Abdulsalam O.A.; Arowolo M.O. (2023). Classification of customer churn prediction model for telecommunication industry using analysis of variance. IAES International Journal of Artificial Intelligence, 12(3), 1323.0-1329.0. doi:10.11591/ijai.v12.i3.pp1323-1329
19. Jajam N.; Challa N.P.; Prasanna K.S.L.; Deepthi C.H.V.S. (2023). Arithmetic Optimization With Ensemble Deep Learning SBLSTM-RNN-IGSA Model for Customer Churn Prediction. IEEE Access, 11(nan), 93111.0-93128.0. doi:10.1109/ACCESS.2023.3304669
20. Elgohary E.M.; Galal M.; Mosa A.; Elshabrawy G.A. (2023). Smart evaluation for deep learning model: churn prediction as a product case study. Bulletin of Electrical Engineering and Informatics, 12(2), 1219.0-1225.0. doi:10.11591/eei.v12i2.4180
21. Consonni C.; Brugnara M.; Bevilacqua P.; Tagliaferri A.; Frego M. (2023). A new Markov,ÄìDubins hybrid solver with learned decision trees. Engineering Applications of Artificial Intelligence, 122(nan), nan-nan. doi:10.1016/j.engappai.2023.106166
22. Zelenkov Y.A.; Suchkova A.S. (2023). Predicting customer churn based on changes in their behavior patterns. Business Informatics, 17(1), 7.0-17.0. doi:10.17323/2587-814X.2023.1.7.17
23. Arai K.; Fujikawa I.; Nakagawa Y.; Momozaki R.; Ogawa S. (2023). Churn Customer Estimation Method based on LightGBM for Improving Sales. International Journal of Advanced Computer Science and Applications, 14(2), 119.0-125.0. doi:10.14569/IJACSA.2023.0140215
24. Tran H.; Le N.; Nguyen V.-H. (2023). CUSTOMER CHURN PREDICTION IN THE BANKING SECTOR USING MACHINE LEARNING-BASED CLASSIFICATION MODELS. Interdisciplinary Journal of Information, Knowledge, and Management, 18(nan), 87.0-105.0. doi:10.28945/5086
25. De S.; Prabu P. (2023). A Representation-Based Query Strategy to Derive Qualitative Features for Improved Churn Prediction. IEEE Access, 11(nan), 1213.0-1223.0. doi:10.1109/ACCESS.2022.3233768
26. Seymen O.F.; Olmez E.; Dogan O.; Er O.; Hiziroglu A. (2023). Customer Churn Prediction Using Ordinary Artificial Neural Network and Convolutional Neural Network Algorithms: A Comparative Performance Assessment. Gazi University Journal of Science, 36(2), 720.0-733.0. doi:10.35378/gujs.992738
27. Khoh W.H.; Pang Y.H.; Ooi S.Y.; Wang L.-Y.-K.; Poh Q.W. (2023). Predictive Churn Modeling for Sustainable Business in the Telecommunication Industry: Optimized Weighted Ensemble Machine Learning. Sustainability (Switzerland), 15(11), nan-nan. doi:10.3390/su15118631
28. Karanatsiou D.; Sermpezis P.; Gruda D.; Kafetsios K.; Dimitriadis I.; Vakali A. (2022). My Tweets Bring All the Traits to the Yard: Predicting Personality and Relational Traits in Online Social Networks. ACM Transactions on the Web, 16(2), nan-nan. doi:10.1145/3523749
29. Mirza O.M.; Moses G.J.; Rajender R.; Lydia E.L.; Kadry S.; Me-Ead C.; Thinnukool O. (2022). Optimal Deep Canonically Correlated Autoencoder-Enabled Prediction Model for Customer Churn Prediction. Computers, Materials and Continua, 73(2), 3757.0-3769.0. doi:10.32604/cmc.2022.030428
30. Loukili M.; Messaoudi F.; Ghazi M.E. (2022). Supervised Learning Algorithms for Predicting Customer Churn with Hyperparameter Optimization. International Journal of Advances in Soft Computing and its Applications, 14(3), 49.0-63.0. doi:10.15849/IJASCA.221128.04
31. Saias J.; Rato L.; Gon√ßalves T. (2022). An Approach to Churn Prediction for Cloud Services Recommendation and User Retention. Information (Switzerland), 13(5), nan-nan. doi:10.3390/info13050227

32. Bilal S.F.; Almazroi A.A.; Bashir S.; Khan F.H.; Almazroi A.A. (2022). An ensemble based approach using a combination of clustering and classification algorithms to enhance customer churn prediction in telecom industry. PeerJ Computer Science, 8(nan), nan-nan. doi:10.7717/PEERJ-CS.854
33. Rabbah J.; Ridouani M.; Hassouni L. (2022). A New Churn Prediction Model Based on Deep Insight Features Transformation for Convolution Neural Network Architecture and Stacknet. International Journal of Web-Based Learning and Teaching Technologies, 17(1), nan-nan. doi:10.4018/ijwltt.300342
34. Nhu N.Y.; Van Ly T.; Truong Son D.V. (2022). Churn prediction in telecommunication industry using kernel Support Vector Machines. PLoS ONE, 17(5 May), nan-nan. doi:10.1371/journal.pone.0267935
35. Sana J.K.; Abedin M.Z.; Rahman M.S.; Rahman M.S. (2022). A novel customer churn prediction model for the telecommunication industry using data transformation methods and feature selection. PLoS ONE, 17(12 December), nan-nan. doi:10.1371/journal.pone.0278095
36. Abdulsalam S.O.; Arowolo M.O.; Saheed Y.K.; Afolayan J.O. (2022). Customer Churn Prediction in Telecommunication Industry Using Classification and Regression Trees and Artificial Neural Network Algorithms. Indonesian Journal of Electrical Engineering and Informatics, 10(2), 431.0-440.0. doi:10.52549/ijeei.v10i2.2985
37. Mar√≠n D√≠az G.; Gal√°n J.J.; Carrasco R.A. (2022). XAI for Churn Prediction in B2B Models: A Use Case in an Enterprise Software Company. Mathematics, 10(20), nan-nan. doi:10.3390/math10203896
38. Arshad S.; Iqbal K.; Naz S.; Yasmin S.; Rehman Z. (2022). A Hybrid System for Customer Churn Prediction and Retention Analysis via Supervised Learning. Computers, Materials and Continua, 72(3), 4283.0-4301.0. doi:10.32604/cmc.2022.025442
39. Fridrich M.; Dost√°l P. (2022). User Churn Model in E-Commerce Retail. Scientific Papers of the University of Pardubice, Series D: Faculty of Economics and Administration, 30(1), nan-nan. doi:10.46585/SP30011478
40. Usman-Hamza F.E.; Balogun A.O.; Capretz L.F.; Mojeed H.A.; Mahamad S.; Salihu S.A.; Akintola A.G.; Basri S.; Amosa R.T.; Salahdeen N.K. (2022). Intelligent Decision Forest Models for Customer Churn Prediction. Applied Sciences (Switzerland), 12(16), nan-nan. doi:10.3390/app12168270
41. Mirkovic M.; Lolic T.; Stefanovic D.; Anderla A.; Gracanin D. (2022). Customer Churn Prediction in B2B Non-Contractual Business Settings Using Invoice Data. Applied Sciences (Switzerland), 12(10), nan-nan. doi:10.3390/app12105001
42. Ullah I.; Rios A.; Gala V.; McKeever S. (2022). Explaining deep learning models for tabular data using layer-wise relevance propagation. Applied Sciences (Switzerland), 12(1), nan-nan. doi:10.3390/app12010136
43. Moral R.A.; Chen Z.; Zhang S.; McClean S.; Palma G.R.; Allan B.; Kegel I. (2022). Profiling Television Watching Behavior Using Bayesian Hierarchical Joint Models for Time-to-Event and Count Data. IEEE Access, 10(nan), 113018.0-113027.0. doi:10.1109/ACCESS.2022.3215682
44. T√©kouabou S.C.K.; Gherghina »ò.C.; Toulni H.; Mata P.N.; Martins J.M. (2022). Towards Explainable Machine Learning for Bank Churn Prediction Using Data Balancing and Ensemble-Based Methods. Mathematics, 10(14), nan-nan. doi:10.3390/math10142379
45. Zhang T.; Moro S.; Ramos R.F. (2022). A Data-Driven Approach to Improve Customer Churn Prediction Based on Telecom Customer Segmentation. Future Internet, 14(3), nan-nan. doi:10.3390/fi14030094
46. Xiahou X.; Harada Y. (2022). B2C E-Commerce Customer Churn Prediction Based on K-Means and SVM. Journal of Theoretical and Applied Electronic Commerce Research, 17(2), 458.0-475.0. doi:10.3390/jtaer17020024
47. Thakkar H.K.; Desai A.; Ghosh S.; Singh P.; Sharma G. (2022). Clairvoyant: AdaBoost with Cost-Enabled Cost-Sensitive Classifier for Customer Churn Prediction. Computational Intelligence and Neuroscience, 2022(nan), nan-nan. doi:10.1155/2022/9028580
48. Muneer A.; Ali R.F.; Alghamdi A.; Taib S.M.; Almaghthawi A.; Abdullah Ghaleb E.A. (2022). Predicting customers churning in banking industry: A machine learning approach. Indonesian Journal of Electrical Engineering and Computer Science, 26(1), 539.0-549.0. doi:10.11591/ijeecs.v26.i1.pp539-549
49. Wang G.-Y. (2022). Churn Prediction for High-Value Players in Freemium Mobile Games: Using Random Under-Sampling. Statistika, 102(4), 443.0-453.0. doi:10.54694/STAT.2022.18

50. Sina Mirabdolbaghi S.M.; Amiri B. (2022). Model Optimization Analysis of Customer Churn Prediction Using Machine Learning Algorithms with Focus on Feature Reductions. Discrete Dynamics in Nature and Society, 2022(nan), nan-nan. doi:10.1155/2022/5134356
51. Bugajev A.; Kriauziene R.; Vasilecas O.; Chady≈°as V. (2022). The Impact of Churn Labelling Rules on Churn Prediction in Telecommunications. Informatica (Netherlands), 33(2), 247.0-277.0. doi:10.15388/22-INFOR484
52. Ha Thanh N.T.; Vy N.T. (2022). Building a proper churn prediction model for Vietnam's mobile banking service. International Journal of Advanced and Applied Sciences, 9(7), 139.0-149.0. doi:10.21833/ijaas.2022.07.014
53. Khodadadi A.; Hosseini S.A.; Pajouheshgar E.; Mansouri F.; Rabiee H.R. (2022). ChOracle: A Unified Statistical Framework for Churn Prediction. IEEE Transactions on Knowledge and Data Engineering, 34(4), 1656.0-1666.0. doi:10.1109/TKDE.2020.3000456
54. Fareniuk Y.; Zatonatska T.; Dluhopolskyi O.; Kovalenko O. (2022). CUSTOMER CHURN PREDICTION MODEL: A CASE OF THE TELECOMMUNICATION MARKET. ECONOMICS - Innovative and Economics Research Journal, 10(2), 109.0-130.0. doi:10.2478/eoik-2022-0021
55. Mahmood I.N.; Abdullah H.S. (2022). Telecom Churn Prediction based on Deep Learning Approach. Iraqi Journal of Science, 63(6), 2667.0-2675.0. doi:10.24996/ijs.2022.63.6.32
56. Faritha Banu J.; Neelakandan S.; Geetha B.T.; Selvalakshmi V.; Umadevi A.; Martinson E.O. (2022). Artificial Intelligence Based Customer Churn Prediction Model for Business Markets. Computational Intelligence and Neuroscience, 2022(nan), nan-nan. doi:10.1155/2022/1703696
57. AL-Najjar D.; Al-Rousan N.; AL-Najjar H. (2022). Machine Learning to Develop Credit Card Customer Churn Prediction. Journal of Theoretical and Applied Electronic Commerce Research, 17(4), 1529.0-1542.0. doi:10.3390/jtaer17040077
58. Mandiƒá M.; Kraljeviƒá G. (2022). Churn Prediction Model Improvement Using Automated Machine Learning with Social Network Parameters. Revue d'Intelligence Artificielle, 36(3), 373.0-379.0. doi:10.18280/ria.360304
59. Al-Shourbaji I.; Helian N.; Sun Y.; Alshathri S.; Elaziz M.A. (2022). Boosting Ant Colony Optimization with Reptile Search Algorithm for Churn Prediction. Mathematics, 10(7), nan-nan. doi:10.3390/math10071031
60. Kristijansson A.M.; Aegisson T. (2022). Survey on Technique and User Profiling in Unsupervised Machine Learning Method. Journal of Machine and Computing, 2(1), 9.0-16.0. doi:10.53759/7669/jmc202202002
61. √ìskarsd√≥ttir M.; G√≠slad√≥ttir K.E.; Stef√°nsson R.; Aleman D.; Sarraute C. (2022). Social networks for enhanced player churn prediction in mobile free-to-play games. Applied Network Science, 7(1), nan-nan. doi:10.1007/s41109-022-00524-5
62. Ibitoye A.O.J.; Onifade O.F.W. (2022). Improved customer churn prediction model using word order contextualized semantics on customers‚Äô social opinion. International Journal of Advances in Applied Sciences, 11(2), 107.0-112.0. doi:10.11591/ijaas.v11.i2.pp107-112
63. Elyusufi Y.; Kbir M.A. (2022). Churn Prediction Analysis by Combining Machine Learning Algorithms and Best Features Exploration. International Journal of Advanced Computer Science and Applications, 13(7), 615.0-622.0. doi:10.14569/IJACSA.2022.0130773
64. Sudharsan R.; Ganesh E.N. (2022). A Swish RNN based customer churn prediction for the telecom industry with a novel feature selection strategy. Connection Science, 34(1), 1855.0-1876.0. doi:10.1080/09540091.2022.2083584
65. Dalli A. (2022). Impact of Hyperparameters on Deep Learning Model for Customer Churn Prediction in Telecommunication Sector. Mathematical Problems in Engineering, 2022(nan), nan-nan. doi:10.1155/2022/4720539
66. Subramanian R.S.; Prabha D. (2022). Ensemble variable selection for Naive Bayes to improve customer behaviour analysis. Computer Systems Science and Engineering, 41(1), 339.0-355.0. doi:10.32604/csse.2022.020043
67. Vo N.N.Y.; Liu S.; Li X.; Xu G. (2021). Leveraging unstructured call log data for customer churn prediction. Knowledge-Based Systems, 212(nan), nan-nan. doi:10.1016/j.knosys.2020.106586

68. Sucu M.√á.; Unusan C. (2021). Predictions from an Empirical Study in the Turkish Mobile Telecommunications Market on the Determinants of Mobile Customer Churn. Journal of Telecommunications and the Digital Economy, 9(4), 178.0-189.0. doi:10.18080/jtde.v9n4.463
69. Ahn J.; Hwang J.; Kim D.; Choi H.; Kang S. (2020). A Survey on Churn Analysis in Various Business Domains. IEEE Access, 8(nan), 220816.0-220839.0. doi:10.1109/ACCESS.2020.3042657
70. H√∂ppner S.; Stripling E.; Baesens B.; Broucke S.V.; Verdonck T. (2020). Profit driven decision trees for churn prediction. European Journal of Operational Research, 284(3), 920.0-933.0. doi:10.1016/j.ejor.2018.11.072
71. Seyedan M.; Mafakheri F. (2020). Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities. Journal of Big Data, 7(1), nan-nan. doi:10.1186/s40537-020-00329-2
72. Amin A.; Al-Obeidat F.; Shah B.; Adnan A.; Loo J.; Anwar S. (2019). Customer churn prediction in telecommunication industry using data certainty. Journal of Business Research, 94(nan), 290.0-301.0. doi:10.1016/j.jbusres.2018.03.003
73. Parwez M.A.; Abulaish M.; Jahiruddin (2019). Multi-Label Classification of Microblogging Texts Using Convolution Neural Network. IEEE Access, 7(nan), 68678.0-68691.0. doi:10.1109/ACCESS.2019.2919494
74. Ullah I.; Raza B.; Malik A.K.; Imran M.; Islam S.U.; Kim S.W. (2019). A Churn Prediction Model Using Random Forest: Analysis of Machine Learning Techniques for Churn Prediction and Factor Identification in Telecom Sector. IEEE Access, 7(nan), 60134.0-60149.0. doi:10.1109/ACCESS.2019.2914999
75. Ahmad A.K.; Jafar A.; Aljoumaa K. (2019). Customer churn prediction in telecom using machine learning in big data platform. Journal of Big Data, 6(1), nan-nan. doi:10.1186/s40537-019-0191-6