Unveiling Persian Market Dynamics: A Comprehensive Analysis of Consumer Demand Using NLP Techniques with Explainable Artificial Intelligence

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ABSTRACT

The Persian language, spoken by more than 110 million people globally, ranks as the 18th most spoken language worldwide. However, the development of Natural Language Processing (NLP) techniques for Persian faces challenges due to limited annotated datasets, dialect diversity, and its complex morphology and syntax. This study addresses this gap by using NLP techniques to analyze market demand in Persian. The research includes sentiment analysis, named entity recognition (NER) and gender prediction to offer insights into consumer preferences.The paper proposes ParsBERT model for sentimental analysis of Persian texts. The data set is collected from various social media platforms, focusing on user reviews of laptop brands and labeled with negative, positive and neutral comments. The ParsBERT model and deep learning methods are analyzed using precision, recall, f1 score, and precision metrics. The results show that the ParsBERT model achieved an accuracy of 98%, which is higher than other machine learning and deep learning models for determining the sentiment of social media comments. Additionally, two Explainable AI (XAI) methods, Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), are used to clarify the decision-making process of the proposed model. The results show most preferred brand among both male and female consumers. This research provides valuable information for businesses and policymakers seeking to understand and meet the demands of the Farsi-speaking market.

CCS CONCEPTS

• **Computing methodologies** → **Natural language generation**; **Information extraction**.

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KEYWORDS

Persian language, Natural Language Processing, market demand, sentiment analysis, NER, gender prediction, XAI, SHAP, LIME.

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1 INTRODUCTION

Persian Language is spoken by over 110 million people around the world, making it the 18th most spoken language in the world [16]. Persian language is the national language of Afghanistan, Iran, and Tajikistan also known as Dari, Farsi, and Tajik but little progress has been made in developing NLP techniques for Persian language [2]. This is mainly due to its lack of available annotated dataset, diversity in dialects, and its complexity in morphology and syntax making it difficult to conduct sentiment analysis. As a result of these barriers, little work has been done in Persian NLP in comparison to languages such as the English language that has made good progress due to its value to businesses and its impact on market demand. However, more demand for this work in English language does not reduce the significance of dynamic Persian market demand.

In recent years, the use of NLP techniques has emerged as a promising new method for analyzing consumer demand. Sentiment analysis, a subfield of NLP, focuses on eliciting consumer opinions, emotions, and preferences. These advances in sentiment analysis are opening up new possibilities for businesses. We can track customer satisfaction, identify problems with products or services, and target our audience effectively. Knowing customer preference will inform our insights into market demand for both old business and new business in today's competitive market. Furthermore, it is crucial to understand market demand for better policy and strategic decisions.

For this purpose, We applied an automatic data scraping method to collect raw text data from YouTube. This method is used for exploring consumer's behavior in the context of online buy and sell groups. After completion of data collection, we used natural language processing to filter and organize our data into a well-structured dataset. Furthermore, by applying a fine-tuned ParsBERT model and different machine learning techniques for sentiment analysis, Named Entity Recognition(NER), and gender prediction. Finally, we implemented two of the famous XAI method called LIME and SHAP to helps in illuminating the decision-making process of the model, making the results more transparent and trustworthy.

2 RELATED WORK

In the pursuit of understanding Persian market dynamics and consumer demand, we draw upon the extensive body of literature that has shaped our research. This section provides an overview of key works from various papers related to our research.

In this paper [7], the researchers conducted a demand analysis in the Bangladeshi smartphone market, employing NLP and machine learning models. Their study yielded impressive results, with an accuracy rate of 87.99 percent achieved in Spacy Custom NER, 95.51% in Amazon Comprehend Custom NER, and 87.02% in the Sequential method for analysis of demand. Notably, the research also introduced an effective approach for addressing misspelled words, successfully rectifying 80% of such errors by combining Levenshtein distance and ratio algorithms. These findings highlight the immense potential of NLP and machine learning in extracting valuable insights regarding consumer preferences and market demand, particularly in regions characterized by linguistic diversity, such as Bangladesh.

In another study [13], researchers discuss sentiment analysis, which involves automatically identifying whether a subject's feelings are positive, negative, or neutral toward something like a topic or product. They note that while deep learning is increasingly used for accurate sentiment analysis in English, there's a need for similar approaches in other languages. The authors propose a new method in Persian movie reviews, using deep learning models such as CNN and LSTM for sentiment analysis. Their results show that LSTM performs better than other models like multilayer perceptron (MLP), autoencoder, SVM, logistic regression, and CNN, suggesting the effectiveness of deep learning in this context.

In this paper [17], the authors delve into sentiment analysis and opinion mining, vital fields that explore people's sentiments and opinions through written language. They highlight the expanding significance of these studies, stretching from computer science to management and social sciences, due to their relevance in business and society. The paper specifically addresses the challenge of sentiment analysis in Persian and proposes a solution using the BERT algorithm. Their experiments show promising results, demonstrating significant improvement in sentiment analysis accuracy for Persian text, especially with the ParsBERT model, achieving high F1 scores and accuracy rates.

In this paper [9], the authors delve into sentiment analysis, a crucial method in NLP for evaluating emotional tones in text. They highlight its importance for businesses in understanding customer sentiments and improving offerings. The survey explores various application domains, pre-processing techniques, and machine learning approaches in sentiment analysis, along with their strengths and limitations. Additionally, it reviews recent state-of-the-art articles, discusses obstacles, and proposes future research work, giving a comprehensive overview of sentiment analysis.

In this paper [3], the authors tackle the challenge of handling vast customer opinions for informed decision-making and product improvement. They extend a sentiment lexicon for Persian text analysis with idiomatic expressions and propose an algorithm for accurate classification. Experimental results demonstrate its superiority over existing methods, with plans to make the lexicon publicly available.

The paper [14] reviews recent studies on sentiment analysis in Persian, focusing on methods, datasets, and algorithm accuracy. It analyzes 40 approaches, highlighting the effectiveness of transformer models and recurrent neural networks. Additionally, it examines Persian language sentiment classification datasets from 2018 to 2022, providing insights into the field's progress and challenges.

In this paper [6], the authors explore the use of deep learning methods for sentiment analysis in Persian language, leveraging the abundance of user-generated content on platforms like Telegram and Twitter. They developed a hybrid deep learning model, incorporating various neural networks and regularization techniques, to analyze customer reviews from Digikala Online Retailer. Their approach demonstrated strong performance, achieving an F1 score of 78.3% across positive, negative, and neutral sentiment categories.

In this paper [10] the authors thoroughly investigate sentiment classification, a technique in natural language processing that identifies emotions in text data. They emphasize its importance for businesses in understanding customer sentiments and making informed decisions. The study explores various applications, pre-processing techniques, and models like ML and DL. It also reviews recent research, highlighting challenges and proposing future directions. Overall, the paper offers a comprehensive understanding of sentiment analysis, its applications, challenges, and avenues for further research.

To illustrate more in the Persian language, researchers have conducted various studies, making significant progress in understanding this complex and nuanced language. To begin with, [12] the author introduces the JAMFA dataset, which includes 2,350 emotionally labeled sentences from Persian literature. This dataset significantly enhances sentiment analysis in Persian. By combining human intelligence with automated methods, the authors achieved a 92% accuracy rate in emotion labeling. Their optimized BERT-BiLSTM model effectively classified basic emotions with 88% accuracy. This research not only fills a gap in Persian emotional corpora but also provides a valuable resource for understanding consumer sentiments, crucial for market demand analysis.

Similarly, another study [8] introduces "LearnArmanEmo," a new dataset that merges existing datasets focused on Farsi and Dari dialects, addressing the unique emotional expressions found in these languages. The authors propose a hybrid model combining XLM-RoBERTa-large and BiGRU, achieving impressive F1 scores that highlight its effectiveness in emotion detection. This research enhances the understanding of emotional nuances in Persian text and lays the groundwork for more accurate sentiment analysis applications, which are crucial for market demand analysis in the region.

In addition, other authors [11] explore the conversion of Persian slang into formal language and its implications for sentiment analysis, particularly within social media contexts. They highlight the challenges posed by informal expressions and shorthand writing in Persian, which complicate sentiment classification. By developing a tool for transforming colloquial texts into formal expressions, the study addresses a significant gap in the existing literature. The authors utilize a comprehensive dataset of over 20 million texts, demonstrating the effectiveness of their approach in enhancing sentiment analysis accuracy. This work underscores the importance of refining natural language processing techniques to better understand market demand through emotional content in Persian texts.

This study [4] introduced a comprehensive framework for detecting harmful language on social media, suitable for any language. It included a detailed interpretation guideline and integrates sentiment analysis. Using the collected Persian dataset, the framework achieved 99.4% accuracy in aggressive language recognition and 66.2% accuracy in sentiment analysis through machine and deep learning methods.

In another work [5], the research investigates graph machine learning methods for text classification on datasets for low resource languages, such as the Persian Digikala dataset. It combines ParsBERT with different graph neural network architectures (GCN, GAT, GIN) and learning techniques. The results show that GNN models improve classification accuracy by better capturing text relationships, and ParsBERT provides better results than general models such as BERT by capturing language-specific details.

Similarly, in another work [15] the research combined Naive Bayes, a custom rule-based model, and BERT to improve sentiment analysis for Persian Twitter. Their hybrid model achieved 89% accuracy, beating BERT's 86%, showing that combining these models can effectively enhance sentiment classification.

Last but not least, researchers introduced [1] the PRFashion24 dataset, a pioneering resource for sentiment classification of fashion product feedbacks in Persian, comprising 767,272 reviews from various online stores. Applying the state-of-art deep learning techniques, including LSTM and BiLSTM-CNN models, the present study obtained the efficiency rate of 81.23% and 82.89% respectively. The results reveal a generally favorable perception of online fashion shopping, which enables the analysis of consumer behavior and increases the knowledge of the market need in the Persian fashion industry. This dataset serves as a significant contribution to the field, facilitating further research in sentiment analysis and consumer behavior in Persian environments.

Utilizing advanced deep learning techniques, specifically LSTM and BiLSTM-CNN models, the research achieved accuracy rates of 81.23% and 82.89%, respectively. The findings highlight a predominantly positive sentiment towards online fashion shopping, providing valuable insights into consumer attitudes and enhancing the understanding of market demand in the Persian fashion industry. This dataset serves as a significant contribution to the field, facilitating further research in sentiment analysis and consumer behavior in Persian contexts.

3 METHODOLOGY

The purpose of this study is to look at the genders of social media users and the customer demand for various laptop brands in Persian. Additionally, the study uses various NLP methods to determine the most popular laptop brand in the Persian-Speaking region. As shown in Fig. 1, the primary components of our system are sentiment analysis, named entity recognition, and gender prediction.

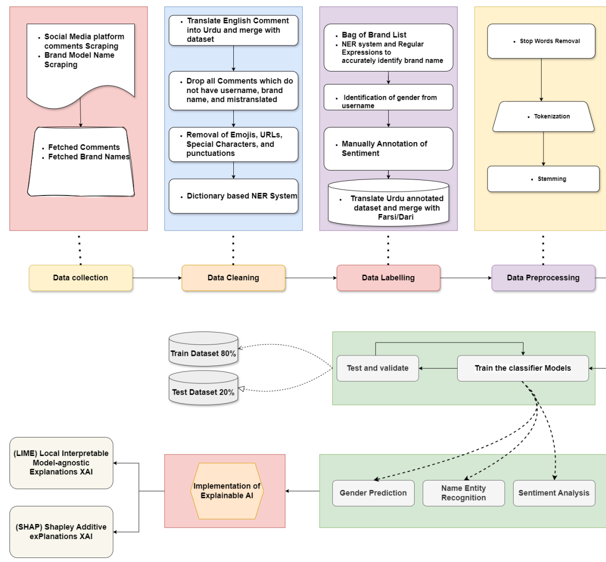

Figure 1: Flowchart of the proposed methodology.

To achieve the research objective, a multi-faceted data collection strategy was employed. Laptop-related comments from YouTube channels and Facebook public pages were utilized to gather consumer preferences and reviews. Additionally, Urdu data was collected and translated into Persian for inclusion in the project. The Instant Data Scraper tool was employed to efficiently gather comments from various social platforms, ensuring a diverse dataset for analysis. Laptop brand and model names were obtained from Wikipedia using a Python web scraper. The obtained model names were then translated using the Google API to ensure data consistency.

An important stage in the process was the creation of a function that used a dictionary-based system to match laptop brand and model names with the collected comment data. The comments were segregated into separate Persian and English segments. Translations were performed from English to Persian to ensure that both language sources were consistent. Data cleaning procedures were carried out to remove rows lacking usernames and comments that did not mention any laptop brands.

To gauge consumer sentiments, the collected comments were categorized into negative, positive, and neutral sentiments. This classification was carried out with the help of local Persian speakers to ensure proper emotion labeling. Various NLP techniques were employed for data preprocessing, including tokenization, stop word removal, and stemming. The dataset was then split into training and test sets for sentiment analysis.

The gender of social media users was predicted using the gender guesser Python library. Because Persian names were not supported, they were converted to English using the Google Cloud Translation API. Gender prediction was based on analyzing only the first names of users. This step aimed to add another layer of understanding by exploring the relationship between gender and consumer opinions.

The collected data underwent comprehensive cleaning and preprocessing using a combination of NLP techniques. Sentiment analysis was performed using both traditional ML and DL models, allowing for a thorough exploration of sentiment trends across different laptop brands.

The results of the analysis were presented in the form of insightful visualizations, which included a list of the top demanding laptop devices based on gender in the present market. These visual representations allowed for a quick grasp of market dynamics and consumer preferences.

Through the execution of this methodology, robust datasets were constructed, capturing and analyzing consumer demand for laptop brands in Persian languages. The research yielded valuable insights into consumer preferences and behaviors, providing a deeper understanding of the market landscape in Persian-speaking regions.

In short, this comprehensive methodology employed a combination of NLP techniques to analyze consumer opinions and genders related to laptop brands in Persian-speaking regions. The strategic data collection, NER, sentiment analysis, and gender prediction allowed for a holistic exploration of the market dynamics, contributing to a better understanding of consumer preferences and behavior in this context.

3.1 Data collection

In order to provide a suitable quantitative foundation for the assessment of consumer demand in Persian-speaking regions, two main datasets were developed. The first dataset was formed of customer product reviews, which represented the textual data needed for sentiment analysis. The second type of data involved laptop brand names extracted from Wikipedia to minimize ambiguous identification of brands for association with the sentiment analysis. This established a double-dataset framework, which helped to compensate for the lack of pronounced structure in the field of Persian consumer demand research.

3.2 Data Cleaning

The data collection strategy employed in this study was multifaceted, ensuring a diverse and representative dataset. Laptop-related comments were gathered from a variety of sources, including YouTube channels and Facebook pages, where consumer preferences and opinions were openly shared. Additionally, the study Urdu data were collected and translated into Persian for inclusion in the project, ensuring that a wide range of opinions and preferences were captured. The Instant Data Scraper tool was employed to efficiently collect comments from various social platforms, providing a rich collection of data for analysis. Moreover, laptop brand and model names were extracted from Wikipedia using a Python web scraper, adding a layer of specificity to the analysis. To guarantee data consistency, model names were translated using the Google API. Following rigorous preprocessing procedures, a meticulously labeled dataset was compiled, containing a total of 2500 entries. This dataset was enriched with sentiment, gender, and product entity information, allowing for a comprehensive analysis of consumer opinions, demographics, and their associations with specific laptop brands. This labeled dataset formed the cornerstone of the subsequent analysis, enabling insightful findings to emerge.

Our paper particularly benefits from defragmented and improved quality of the collected data. In this part, we explain the conscientious process that has been followed so that all the subsequent analysis should be feasible on the data obtained. In our analysis, we were able to systematically filter out punctuation, special characters, and emojis from the Persian dataset using the regular expression library of Python. This did not only make the dataset cleaner but also aligned with a standard baseline, which excluded unwanted information.

Furthermore, the stop words from persian text removed to reduce noise. Leveraging the Persian NLP Toolkit, Hazm, allowed us to seamlessly eliminate these frequently occurring words, consequently elevating the overall quality of the text data and bolstering the accuracy of subsequent analyses.

3.3 Data Labelling

The cleaned data was manually labeled for sentiment positive, negative, and neutral by native Persian speakers. This labeling was crucial for training the sentiment analysis model accurately.

3.4 Data Preprocessing

Segmentation of text into individual tokens, known as tokenization, was another pivotal step in our preprocessing pipeline. By dividing comments into their constituent parts, we paved the way for in-depth examination and analysis of the textual content. This process proved instrumental in preparing the text data for extensive language processing.

Moreover, the tokenized language was standardized through the application of stemming techniques. This practice involved converting words to their base or root forms, effectively minimizing word variants and ensuring consistency throughout the dataset. Our systematic removal of prefixes and suffixes contributed to presenting words in their most fundamental structures.

The culmination of these preprocessing stages resulted in the creation of a meticulously refined dataset. From data collection and punctuation removal to stop-word elimination, tokenization, and stemming, each step was diligently executed to cultivate a dataset primed for insightful analysis. This polished dataset, a valuable asset, empowered our sentiment analysis efforts, enabling us to extract meaningful insights into consumer dynamics within the Persian-speaking market. Through this comprehensive data preparation process, we laid a robust foundation for exploring consumer preferences and behaviors, underscoring the significance of proper data preprocessing in our study.

3.5 Data Splitting

The dataset was split into train and test set 80% is for training and 20% for testing. This split ensured that the model could be trained, and tested on various subsets of data, to limit the risk of overfitting.

4 NAMED ENTITY RECOGNITION

The vast amount of textual material on the internet, including sites like Facebook, blogs, and Wikipedia, is a true goldmine of knowledge. The constant evolution of techniques, algorithms, and tools to extract valuable insights from this ever-expanding digital landscape underscores the importance of Named Entity Recognition (NER). NER plays a pivotal role in identifying noun entities, including names, dates, times, and locations. In this study, we used a dictionary-based NER system to extract names of different laptop brands names from user comments on social media. This task holds fundamental significance within the domain of NLP. Notably, our experiment encompassed laptop brand names in both the English and Persian languages. To address this multilingual challenge, we developed a bilingual dictionary-based system capable of effectively accommodating both linguistic contexts.

It is imperative to acknowledge that customers often employ diverse writing styles when referring to the same brand names. For instance, the brand HP may be represented as Hp, hp, hP, and many more. In recognition of this variation, our dictionary-based NER model was meticulously crafted to accurately identify different writing styles associated with each brand. This approach was thoughtfully designed to ensure precise extraction of brand names from user comments, even when expressed in various linguistic variations.

In line with this methodology, our NER algorithm was customized to recognize specific terms linked to individual brands. Additionally, we developed a function through manual coding and regular expressions. This function harnessed the dictionary-based approach to match device names by comparing the laptop list with the content of the comments.

5 GENDER PREDICTION

Understanding the gender base variations in product demand is essential for the business, As gender preferences exhibit significant diversity. In our research, we used three gender prediction libraries to identify the gender from the username. Initially, our approach involved the utilization of the Python gender guesser package, a tool designed to infer user genders based on given names. However, we encountered a various challenge along the way. The Python gender guesser package, while robust for many purposes, did not possess the capability to handle Persian names effectively. Recognizing the importance of inclusivity, we found a solution. To bridge this linguistic gap, we turned to the Google Cloud Translation API. This powerful tool allowed us to translate Persian names into English, rendering them compatible with the gender guesser package.

To further enhance our gender prediction accuracy, we conducted a comparative analysis. We leveraged two additional libraries, Genderizer and gender_guess, to assess the performance of our prediction model. This meticulous evaluation allowed us to fine-tune our approach and achieve improved results. Despite our diligent efforts to overcome this language barrier, we encountered persistent inaccuracies in gender predictions. These discrepancies underscored the complexity of the task at hand. In response, we adopted a refined strategy. We decided to exclusively rely on individuals' first names for gender prediction, simplifying the process while maintaining a degree of accuracy.

Through this evaluation and iterative improvements, we honed the gender prediction component of our approach. The result was an effective and reliable method for predicting gender based on first names, enhancing the precision of our analysis. The distribution of gender in the dataset is shown in Fig. 2.

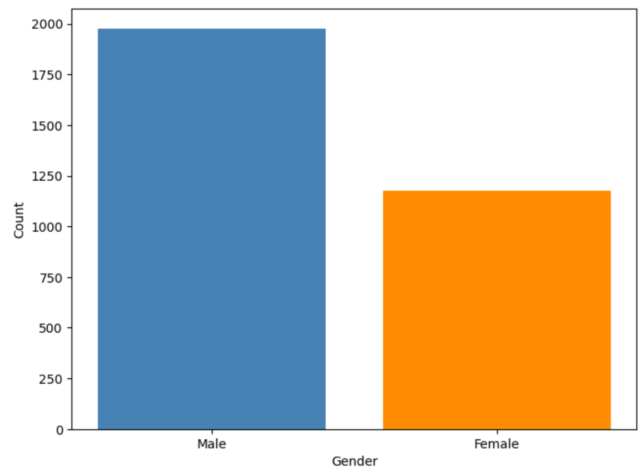

Figure 2: Distribution of gender in the dataset.

6 PROPOSED MODEL

The proposed model uses ParsBERT, a pre-trained BERT model specifically designed for Farsi text, which we fine-tuned to analyze sentiment on social media reviews.

In the first step, we loaded the pre-trained ParsBERT model and its tokenizer, using the Transformers library. Then, the dataset is prepared for the BERT model including converting the text into input IDs and attention masks, which are necessary for the BERT model. Additionally, data loaders were designed to efficiently feed data into the model during training and evaluation. The maximum length of the tokenized input sequence was set to 128 and the batch size was set to 16. Additionally, the model was trained with the AdamW optimizer with a learning rate of 2e-5. The training loop included forward propagation, loss calculation, back propagation, and optimization steps and the model was trained for 10 epochs. Finally, model performance on the validation set was evaluated using metrics such as precision, accuracy, recall, and F1 score. Fig. 3 presents the confusion matrix for the proposed model.

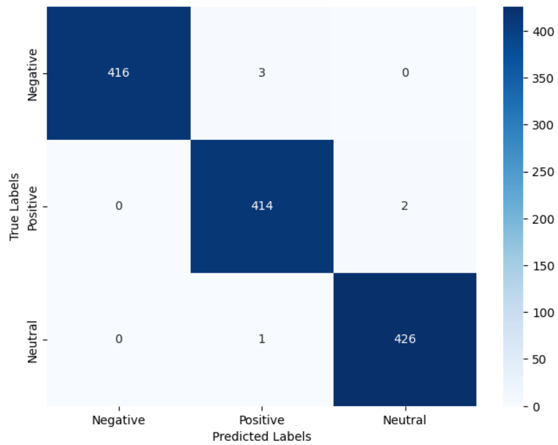

Figure 3: Confusion matrix for proposed model.

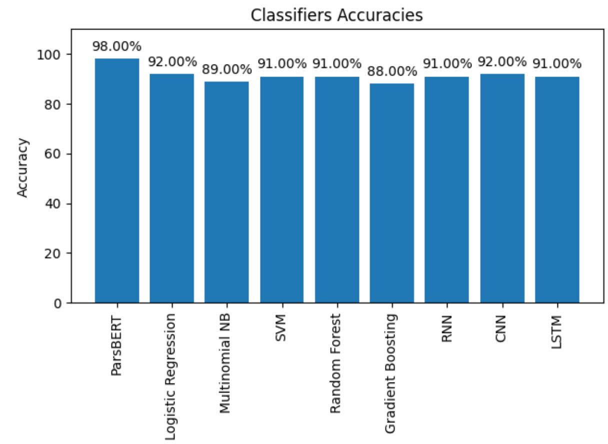

Figure 4: Classifier accuracy comparison with ParsBERT.

7 SENTIMENT ANALYSIS

In the task of sentiment analysis we evaluated the effectiveness of ParsBERT, ML and DL models using four performance metrics; precision, recall, F 1 score and accuracy. Table 1, below, presents a summary of the results obtained from evaluating these models on the task of sentiment analysis and the bar chart in Fig. 4 shows classifier accuracies. The table demonstrates how each model performs across these metrics. Notably, ParsBERT perform very well across all performance metrics; precision 99%, recall 98%, F 1 Score 98% and accuracy 98%. Both the Multinomial logistic regression and SVM models show precision, recall, F 1 score and accuracy scores ranging from 91% to 92%. The Random Forest model also exhibits performance with a Score of 91% and an accuracy score of 91%. Although the Gradient Boosting model slightly falls behind with a score and accuracy score of 88% it still maintains results. Moreover, the Multinomial NB model delivers slightly lower scores across all metrics at 89%. The RNN, CNN, and LSTM models consistently perform well with precision, recall, F 1 score and accuracy values all at 91%. These findings show the competence of ML and DL approaches in sentiment classification. They also give a foundation for discussions on selecting models, for sentiment classification applications.

Table 1: Performance comparison of various models.

Models	Precision	Recall	F-1 Score	Accuracy
Multinomial LR	91	91	92	92
SVM	92	91	91	91
Multinomial NB	89	89	89	89
Random Forest	93	91	91	91
Gradient Boosting	89	88	88	88
RNN	91	91	91	91
CNN	92	92	92	92
LSTM	91	91	91	91
ParsBERT	**99**	**98**	**98**	**98**

8 IMPLEMENTATION OF EXPLAINABLE AI

Explainable AI (XAI) purpose is to make understandable the process of how a model works. This explains the reasoning behind the categorization of certain sentiments. The XAI methods helps in illuminating the decision-making process of the model, making the results more transparent and trustworthy.

8.1 LIME

Local Interpretable Model-Agnostic Explanations (LIME) was used to interpret the predictions of the fine-tuned ParsBERT model, providing insights into which parts of the text contributed most to the sentiment classification.

For example, in Fig. 5, the sentence (Lenovo laptops offer great multitasking performance) was initially classified as having a positive sentiment. This is because there are some positive word was highlighted here.

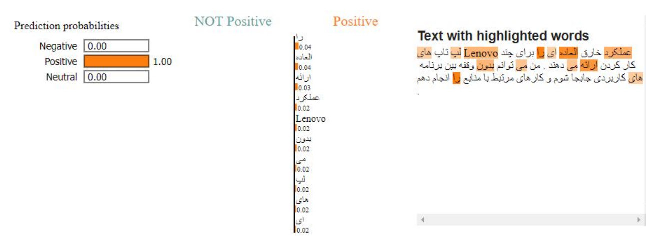

Figure 5: LIME XAI result for positive sentiment.

Moreover, the Fig. 6 would provide us a sentence (Dell laptops come with a limited choice of screen resolution, which hinders image and quality descriptions.) with negative sentiment where the word (limited) with negative sentiment where the word (limited) is associated with negative sentiment. which means "not enough" or "restricted." In the context of the sentence, it is used to describe the choice of screen resolutions available on Dell laptops. The fact that the choice of screen resolutions is limited means that users are not able to choose the resolution that best meets their needs. This can be a negative experience for users who are looking for a laptop with a high-quality display.

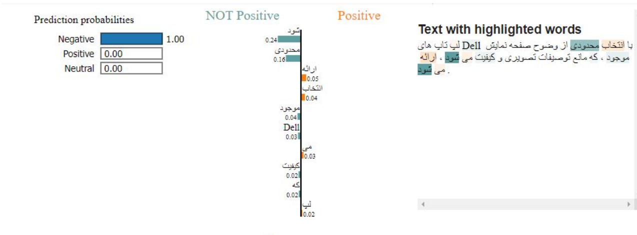

Figure 6: LIME XAI result for negative sentiment.

Finally, the Fig. 7 (Does the battery last longer on the HP Specter X 360?) Here the sentence is neutral due to the (does) which is a question word and does not express any feeling, emotion or opinion. it's simply asking about the battery life of HP specter X360, therefore its neutral sentence.

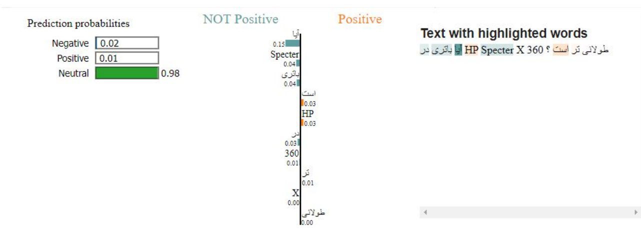

Figure 7: LIME XAI result for neutral sentiment.

9 SHAP

The Fig. 8 shows SHAP XAI results for both positive and negative sentiment predictions. The top graph shows how specific features contributed to predicting a positive sentiment, with red segments pushing towards positivity and blue segments pulling away from it. The bottom graph illustrates the opposite for negative sentiment, where red segments increase negativity, and blue segments reduce it. The final values show how these features influenced the model's output for each sentiment, providing clear insight into which inputs had the most impact on the prediction.

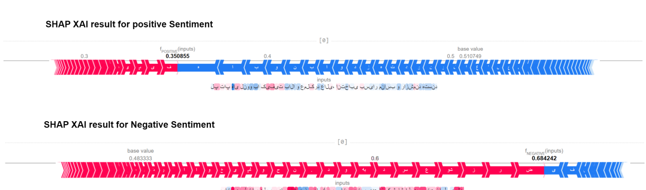

Figure 8: SHAP XAI result for positive and negative sentiment.

Fig. 9 shows the influence of various features on the model's output using Shapley Additive Explanations (SHAP) values. Each feature is listed on the y-axis, and the x-axis shows its SHAP value, indicating whether the feature pushes predictions positively or negatively. The dots, colored from blue (low value) to red (high value), represent individual data points, demonstrating the distribution and impact of feature values. A wider spread along the x-axis suggests higher variability in the feature's influence on the model's predictions.

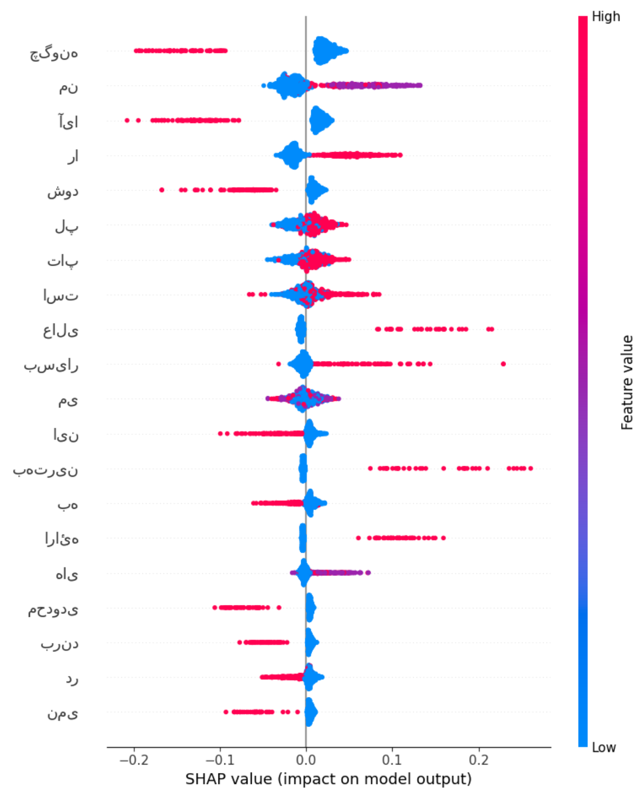

Figure 9: SHAP XAI result for positive sentiment.

10 DEMAND ANALYSIS

In the pursuit of a comprehensive understanding of consumer demand in the laptop market, we conducted an in-depth analysis that shed light on the preferences of both male and female consumers. Our analysis revealed intriguing insights into the popularity of laptop brands and specific laptop models in Persian-speaking region.

We initiated our analysis by examining the popularity of laptop brands among male and female consumers. To visualize this, we generated a stacked bar chart and pi chart illustrating the top nine laptop brands in Fig. 10 and 11 based on demand. The results indicated that Lenovo emerged as the most preferred laptop brand, followed closely by Dell, HP, Apple, Asus, and Acer, in both male and female consumer segments. This consistent ranking across genders highlights the universal appeal of these brands in the laptop market.

The demand analysis not only underlines the dominance of certain laptop brands but also highlights the significance of understanding the finer nuances in consumer preferences. Such insights

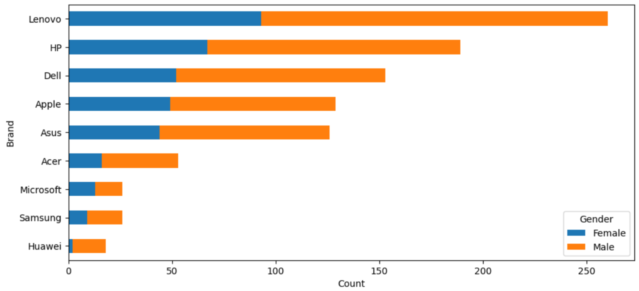

Figure 10: Top 9 laptop brands among male and female.

are invaluable for businesses and policymakers looking to tailor their products and strategies to better meet the needs and desires of their target audience.

In conclusion, our demand analysis provides a comprehensive view of the laptop market, revealing the hierarchy of popular brands and specific laptop models among male and female consumers. These findings can serve as a foundation for informed decision-making, helping businesses navigate the dynamic landscape of consumer demand effectively.

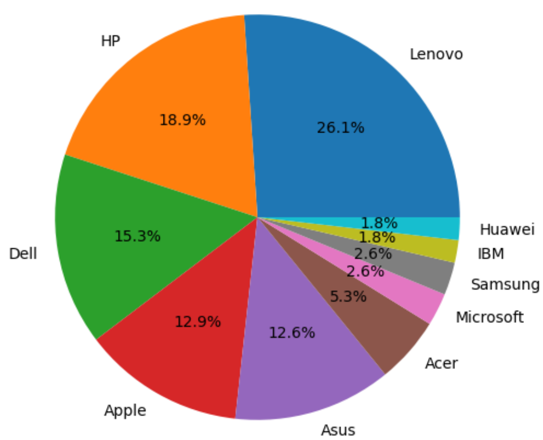

Figure 11: Top ten brands for positive sentiment.

11 CONCLUSION

In this paper we unveiled the market demand among Persian native speakers around the world by using NLP techniques which is greatly affecting business in the market. And by using NLP and ML techniques mainly gender prediction and NER model we could have a well-structured and trained dataset. After we applied ParsBERT, ML and DL models, which were unable to give us valuable insights about the most popular products based on gender and sentiment analysis. Finally, we have implemented the two of XAI methods LIME and SHAP to clarify the decision-making process of the proposed model.

12 FUTURE WORK

In this paper, we investigate the demand of the Persian market by using social media comments. We would like to expand our work in future in a larger scale of dataset which allows us to widen insight to the Persian market. Additionally, we plan to develop more adaptive models that can handle different dialects and regional variations within the Persian language, making our models more robust and accurate. Also, the SHAP and LIME XAI methods can be used for various tasks. We intend to apply it to other tasks such as sentiment analysis and age prediction.

13 ACKNOWLEDGMENTS

ChatGPT was utilized to generate sections of this Work, including text, and citations.

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