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Textual Taste Buds: A Profound Exploration of Emotion Identification in Food Recipes through BERT and AttBiRNN Models

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Abstract: Sentiment analysis of food reviews has become increasingly vital in understanding customer preferences and enhancing the food and hospitality industry's offerings. However, conducting precise sentiment analysis in this context, particularly with five distinct sentiment classes (very negative, negative, neutral, positive, and very positive), poses significant challenges. This paper addresses these challenges by proposing an advanced approach for five-class sentiment analysis. Leveraging state-of-the-art natural language processing techniques, we explored various models, including RNN, BiRNN, AttBiRNN, and BERT. Our results indicate that BERT, with its bidirectional contextual understanding, outperformed the other models, achieving the highest accuracy and F1 score. AttBiRNN also demonstrated strong performance. This research contributes to the field of sentiment analysis, providing valuable insights into customer sentiments within the food and hospitality industry and emphasizing the efficacy of advanced models like BERT for fine-grained analysis.

***Keywords*:** Food Review, Deep Learning, Sentiment Analysis, BERT

1. INTRODUCTION

In an era characterized by an unprecedented explosion of online content, social media, and e-commerce, understanding and interpreting customer sentiments has become paramount for businesses across industries. Sentiment analysis, a subfield of natural language processing (NLP), plays a pivotal role in deciphering the sentiments, opinions, and emotions expressed in textual data. It enables organizations to glean invaluable insights from the vast sea of customer reviews, social media comments, and textual feedback, ultimately aiding in informed decision-making and enhancing customer experiences [1].

The essence of sentiment analysis lies in categorizing text data into predefined sentiment classes that encapsulate the emotional tone of the text. Among the various applications of sentiment analysis, one area that has gained substantial attention is the evaluation of customer sentiment in the context of product reviews. In particular, the food and hospitality industry has witnessed an unprecedented surge in customer-generated content, making it a fertile ground for sentiment analysis.

Within the realm of food reviews, understanding customer sentiments is not merely an academic exercise but a business imperative. It can provide crucial insights into customer preferences, satisfaction levels, and areas of improvement for restaurants, food delivery services, and culinary establishments. To address this, our study focuses on the sentiment analysis of food reviews, aiming to categorize customer sentiments into five distinct classes: "very positive", "positive", "neutral", "negative," and "very negative."

To accomplish this task, we employ a diverse range of state-of-the-art NLP models, including Recurrent Neural Networks (RNNs), Bidirectional Recurrent Neural Networks (BiRNNs), Attention-based Bidirectional Recurrent Neural Networks (AttBiRNNs), Bidirectional Encoder Representations from Transformers (BERT). These models have demonstrated remarkable proficiency in natural language understanding tasks and are well-suited for the complexity of sentiment analysis.

The subsequent sections of this paper will delve into the Literature Review, System Architecture, Results, and discussions, providing a holistic view of our findings and their implications. Through this study, we strive to advance the field of sentiment analysis and offer practical guidance for its application in the dynamic landscape of food and hospitality.

2. LITERATURE REVIEW

Researchers have been actively engaged in studying sentiment analysis, which has emerged as a prominent area of investigation in recent years. In their work, authors [2] emphasize the three fundamental aspects of sentiment analysis: positive, negative, and neutral sentiments. Over the past few years, the World Wide Web has assumed a pivotal role in shaping customer reviews. Through platforms like social media and e-commerce websites such as Facebook and Twitter, users have the opportunity to express their opinions through reviews, which can range from favorable to unfavorable. These user-generated reviews play a crucial role in influencing decisions related to the implementation of new strategies and product choices.

In this study [3], the authors did a comprehensive survey of various sentiment analysis studies. The study concluded by emphasizing that there is still significant potential for further advancement in the fields of sentiment classification and feature extraction techniques. Up to the present time, the most widely utilized machine learning algorithms for sentiment classification have been Naïve Bayes and Support Vector Machine (SVM). Additionally, it was noted that WordNet stands out as the most prevalent lexicon, primarily due to its availability in languages other than English.

In this study [4], the authors focused on the analysis of product reviews sourced from Amazon. The primary objective of their research was to detect and identify negation phrases within these reviews. This analysis encompassed both sentence-level and review-level classifications of the data and pertained to reviews collected during the period spanning from February to April in the year 2014.

In this study [5], the authors delve into the dynamic domain of sentiment analysis, particularly focusing on sentiment expressed in food reviews within the context of social media, with Twitter as a central point of exploration. Social media platforms, like Twitter, have brought about a profound shift in how individuals convey their sentiments about food and culinary experiences, rendering them invaluable sources of real-time sentiment data. The sheer volume of user-generated content in these digital spaces presents both challenges and opportunities in deciphering the sentiments prevailing within the online community. Leveraging advanced machine learning techniques, including Support Vector Machines (SVM), Logistic Regression, Random Forest, and Naive Bayes, researchers continually refine their sentiment analysis methodologies to capture the intricate and multifaceted nature of sentiments expressed in food-related discussions on platforms such as Twitter. As this field evolves, its significance persists in aiding businesses, governments, and researchers in distilling meaningful insights from the digital dialogues that shape contemporary discourse in the realm of food reviews.

In this study [6], the authors presented an innovative approach to address the challenges of sentiment analysis in product reviews. Their technique focused on eliminating sentiment-related traits from the product reviews. They achieved this by utilizing TF-IDF vectors, a common approach, while considering synonyms within the product reviews. This allowed them to categorize sequences of feature vectors using clustering algorithms. The result was an improved precision of span algorithms, particularly for detecting consecutive phrases, while preserving the crucial word order details. By implementing these steps, the authors successfully gathered essential text features, leading to enhanced overall performance through the utilization of various mechanisms.

In this study [7], the authors delve into the realm of sentiment analysis with a particular focus on the application of Recursive Neural Networks (RNNs) in the context of Amazon Food Review data. Their study addresses the challenges associated with processing raw text data from these reviews and proposes innovative solutions to tackle these issues. Specifically, they present a novel technique for parsing binary trees using the Stanford NLP Parser, facilitating the transformation of unstructured text into a format suitable for deep learning analysis. Additionally, the authors tackle the problem of insufficient labeling in the original dataset by introducing a unique method for labeling tree nodes. The culmination of their efforts resulted in the development of a cutting-edge model, RNNMS (Recursive Neural Network for Multiple Sentences), which outperforms the baseline model across a spectrum of evaluation metrics. This research contributes significantly to the field of sentiment analysis, providing a robust framework for leveraging deep learning in the analysis of sentiment within Amazon Food Reviews.

In summary, this literature review illuminates the vibrant landscape of sentiment analysis, focusing on its applications in product reviews and food-related discussions. The studies discussed showcase the diverse range of methodologies and machine-learning techniques employed to refine sentiment classification and feature extraction. However, it's crucial to acknowledge the existing limitations, including the need for more extensive cross-linguistic studies, comprehensive algorithm comparisons, and adaptation to evolving digital platforms. These constraints emphasize the evolving nature of sentiment analysis, presenting both challenges and prospects for further research and innovation in the field.

3. SYSTEM ARCHITECTURE

This section furnishes detailed information on data collection, data preprocessing, and the methodology employed in this study.

3.1 Data Collection

In this research, the dataset was sourced from the reputable cooking recipe website tasteofhome [8], comprising comments and reviews associated with the top 100 most popular recipes. We employed the Selenium library to extract the list of ingredients from each HTML page. Regarding the comments, we leveraged the concealed backend API utilized by the website, circumventing the need to load all comments within the HTML pages. In total, we acquired 100 sets of ingredients and 18,182 comments, organized into two CSV files: "ingredients" and "comments." The ingredients file includes recipe names, ingredient lists, recipe codes, and the best score column, which contains food review scores on a scale of 1 to 5. The comments file contains textual information pertaining to food reviews. In this project, we merged both files, utilizing the "review text" column as the predictive attribute and the "best score" column, which categorizes reviews into five classes: "very positive," "positive," "neutral," "negative," and "very negative," as the target attribute for our analysis.

3.2 Data Preprocessing

In the data preprocessing phase for food review sentiment analysis, several key operations were conducted to ensure the text data's suitability for analysis. Initially, all text was converted to lowercase to establish uniformity and simplify subsequent processing. Punctuation, including common punctuation marks, was removed to enhance text consistency. Special characters were eliminated using regular expressions, further cleaning the text. Additionally, numerical digits were removed, as they were deemed irrelevant for sentiment analysis. Subsequently, tokenization was applied to break the text into individual words or symbols, facilitating further analysis. Stop words, such as "A," "The," "IS," and "ARE," were removed to eliminate non-essential words. Finally, lemmatization was performed to derive words into their root forms, aiding in the categorization of synonymous words into a single word form. These preprocessing steps collectively contributed to the preparation of clean and standardized text data for the sentiment analysis of food reviews.

For feature extraction in our sentiment analysis task, we employed Word2Vec, a neural network-based method widely used in natural language processing. Word2Vec learns distributed representations, also known as word embeddings, from extensive unstructured text data. The fundamental concept behind Word2Vec is to utilize a neural network to generate high-dimensional vector representations for each word in the vocabulary. These vectors encapsulate the semantic meaning and contextual information of words, rendering them numerical features suitable for various natural language processing tasks, including sentiment analysis [9]. In our implementation, we harnessed the gensim library in Python to access the Word2Vec model. Word2Vec proves invaluable in feature extraction by furnishing dense vector representations for words, effectively capturing their context, semantics, and interrelationships. This, in turn, enhances the effectiveness of our sentiment analysis.

3.3 Methodologies

3.3.1 RNN

In our sentiment analysis implementation for food reviews, we harnessed the power of Recurrent Neural Networks (RNNs) to predict sentiment scores spanning a range from 1 to 5. RNNs, well-suited for processing sequential data, were an ideal choice for comprehending and analyzing the sequential nature of text data [10]. Our RNN model comprised three key components: an input layer, an RNN layer, and an output layer. The input layer received preprocessed text data as input, while the RNN layer, a recurrent component, captured sequential dependencies within the text data, enabling it to understand the context and nuances of the reviews. The output layer featured five neurons, each representing a sentiment score on our fine-grained scale from 1 (very negative) to 5 (very positive). During training, we utilized a labeled dataset associating each food review with a sentiment score between 1 and 5, reflecting the reviewer's sentiment toward the food. The RNN was trained to predict these sentiment scores directly from the textual content of the reviews, facilitating detailed and fine-grained sentiment analysis.

3.3.2 BiRNN

Bidirectional Recurrent Neural Networks (BiRNNs) a specialized variant of recurrent neural networks, excel in capturing contextual information by processing data both forwards and backward [11-12]. Our BiRNN model was composed of three crucial components: an input layer, a Bidirectional RNN layer, and an output layer. The input layer facilitated the integration of preprocessed text data into our model, while the Bidirectional RNN layer harnessed forward and backward processing to comprehensively capture sequential dependencies, enabling our model to grasp the nuances of sentiment expressions within food reviews. The output layer featured five neurons, each corresponding to sentiment scores on a scale ranging from 1 to 5. Through training on labeled data, where each review was paired with a corresponding sentiment score, the BiRNN performed direct predictions of sentiment scores based on the text content, thereby facilitating precise sentiment analysis.

3.3.2 AttBiRNN

Attention-based Bidirectional Recurrent Neural Networks (AttBiRNNs) a sophisticated variant of recurrent neural networks, adeptly capture contextual information through bidirectional data processing and attention mechanisms [13]. Our AttBiRNN model comprised three pivotal components: an input layer, an Attention-based Bidirectional RNN layer, and an output layer. The input layer seamlessly integrated preprocessed text data into our model. Notably, the distinctive feature of our approach lay in the Attention-based Bidirectional RNN layer, which not only captured sequential dependencies via bidirectional processing but also employed attention mechanisms to focus on salient elements within the text data, thereby enhancing the model's comprehension of sentiment nuances in food reviews. Similar to previous methods, the output layer featured five neurons, each corresponding to sentiment scores on a scale from 1 to 5. During training, utilizing labeled data associating each review with an appropriate sentiment score, the AttBiRNN made direct predictions of sentiment scores based on the textual content. This methodology facilitated precise sentiment analysis, furnishing comprehensive insights into customer sentiments within food reviews.

3.3.3 BERT

In the realm of sentiment analysis, the last method we employed is an advanced technique known as Bidirectional Encoder Representations from Transformers (BERT). BERT represents a significant advancement in natural language understanding, capable of capturing intricate contextual nuances within text data [14-16]. Our BERT-based model was structured with distinct components, leveraging the power of pre-trained language representations to enhance sentiment analysis. BERT's bidirectional nature allowed it to understand the complete context of words in a sentence, an essential feature for capturing subtle sentiment expressions. The model utilized pre-trained embeddings and fine-tuned them during training to predict sentiment scores. Consequently, our implementation provided comprehensive insights into the sentiments expressed in food reviews, enhancing our understanding of customer opinions in greater detail.

4. RESULT AND DISCUSSION

The presented performance metrics shed light on the effectiveness of various sentiment analysis models in the context of food reviews. Notably, BERT emerged as the standout performer, boasting an Accuracy of 0.75, indicating a remarkable 75% correct prediction rate. Its Recall (0.72) and F1 Score (0.73) were also the highest among the models, underscoring its exceptional ability to accurately identify positive sentiment expressions within the reviews. This superior performance can be attributed to BERT's advanced language understanding capabilities and bidirectional context analysis.

Table 1: Performance Metrics

Models	Accuracy	Recall	F1 Score
RNN	0.69	0.67	0.68
BiRNN	0.70	0.69	0.69
AttBiRNN	0.71	0.68	0.69
BERT	0.75	0.72	0.73

Comparatively, the other models, such as RNN, BiRNN, and AttBiRNN, displayed commendable performance, each with incremental improvements in Accuracy, Recall, and F1 Score. While these models achieved respectable results, they fell slightly short of the precision and recall achieved by BERT. Nevertheless, their performance highlights their suitability for sentiment analysis tasks, offering viable options for extracting sentiment insights from food reviews.

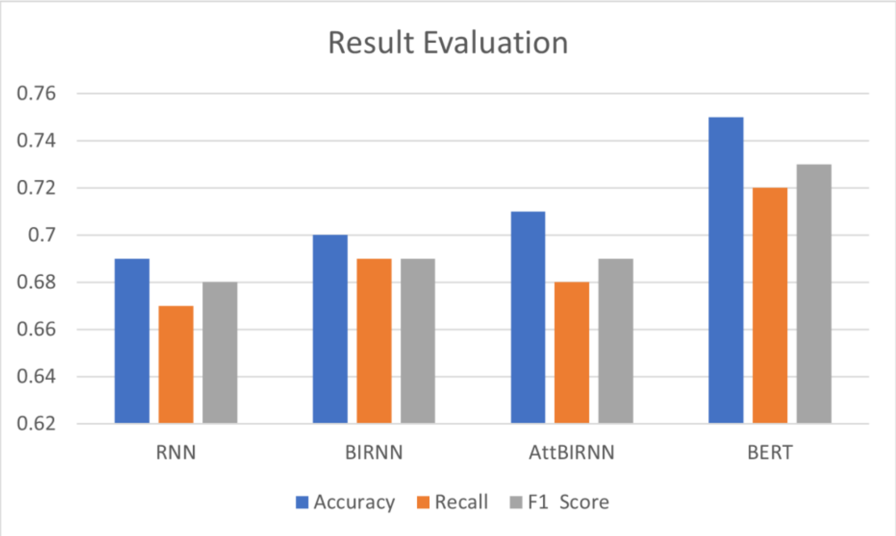

Figure 1: Results Graph

In essence, the results emphasize the pivotal role of advanced natural language processing models like BERT in enhancing the accuracy and depth of sentiment analysis in the realm of food reviews. While BERT excelled in providing nuanced sentiment classification, the other models also demonstrated their capability to contribute valuable sentiment insights, catering to a range of analytical requirements within the food and hospitality industry.

5. CONCLUSION AND FUTURE WORK

In conclusion, our study delved into the intricate task of five-class sentiment analysis for food reviews, aiming to gain a nuanced understanding of customer sentiment within the food and hospitality industry. We employed four distinct models—RNN, BiRNN, AttBiRNN, and BERT—to tackle this challenging task and extract valuable insights from textual customer feedback. Our results painted a clear picture of the models' performance. BERT, with its advanced natural language understanding capabilities, emerged as the standout performer, achieving the highest accuracy, recall, and F1 score among all models. Its ability to capture fine-grained nuances in sentiment expressions within food reviews highlighted its effectiveness in this domain. The significance of our study lies in its demonstration of the capability of advanced natural language processing models, particularly BERT, to handle the complex task of five-class sentiment analysis in the food and hospitality industry. This fine-grained analysis empowers businesses to gain a deeper understanding of customer sentiments, facilitating informed decision-making and improvements in product and service quality. In summary, our research underscores the pivotal role of advanced NLP models in sentiment analysis, offering valuable tools for deciphering customer opinions and sentiments within the ever-evolving landscape of food reviews.

Future work in the domain of sentiment analysis for food reviews presents exciting opportunities for research and practical applications. One avenue for exploration is the integration of multimodal analysis, combining text, images, and audio data to provide a more holistic view of customer sentiments. Additionally, extending sentiment analysis to multilingual reviews, conducting longitudinal studies, and exploring novel techniques for handling evolving customer preferences represent vital paths for future research in this dynamic field.

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