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Analysis of User Sentiment Towards McDonald's on Twitter Using Aspect-Based Sentiment Analysis (ABSA)

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Abstract

This thesis presents a novel Enhanced BERT-Based multi-task classification model for comprehensive sentiment, aspect, and category identification in the context of large-scale social media data. The study is twofold: first, the performance of different model architectures BERT, BERT-BiLSTM, and BERT-BiLSTM-Transformer was systematically compared using detailed metrics and visualizations. The results demonstrated that BERT-BiLSTM-Transformer model, particularly when combined with SMOTE to address class imbalance, outperformed the other architectures, achieving the highest F1-scores across all tasks (Aspect: 0.7756, Category: 0.8457, Sentiment: 0.8563). Second, the model was applied to a dataset of 151,502 tweets about McDonald's aiming to provide insights into public sentiment across pre-defined aspects and categories. The results revealed that while 'Products', 'Food' and 'Loyalty' were most positively perceived, negative sentiment was prevalent in aspects such as 'Customer Service', 'Ethical Responsibility', and 'Public Health Impact'. This study demonstrates the effectiveness of advanced deep learning models in ABSA and offers actionable recommendations for businesses like McDonald's operating in the social media landscape.

1. Introduction

The ubiquitous rise of digital networking technologies such as internet and mobile phones has opened doors to analyzing human behavior with unprecedented level of detail. A wide range of online platforms including internet forums, blogs and social media generate a vast amount of real-time data (Steinert-Threkeld, 2018). The advent and rapid proliferation of social media platforms have further revolutionized the nature of online participation. Social networking as one the fastest-growing industries has attracted a substantial and continuously expanding userbase, with global usage exceeding 5 billion users in 2024 (DataReportal, 2024). Social media platforms have become primary channels for information dissemination and social interaction (Avalle et al., 2024). Driven by potential of deeper insights into evolving dynamics of society and the market, businesses and researchers aim to leverage the unstructured data obtained from social medial platforms (Cano-Martin et al., 2023). They utilize rapid advancements in Artificial Intelligence (AI) and cloud computing technologies, which facilitate the analysis of big data (Mareno & Redondo, 2016).

The number of users on social media platforms, particularly Twitter (rebranded as X) has increased exponentially. With over 300 million active accounts generating more than 300 thousand tweets per minute (Domo, n.d.), Twitter mirrors diverse populations, eliminating the need for large teams of researchers to analyze various segments simultaneously (Steinert-Threkeld, 2018). Its publicly available data, global reach, extensive user base and reputation as general-purpose platform make it a valuable resource for understanding customer sentiment and perception. These insights can contribute to effective decision-making, ultimately boosting productivity (Blumberg & Arte, 2003; Niu et al., 2021; Cano-Marin et al., 2023). Consequently, Twitter was selected as the primary data source for this study due to its exceptional capability to provide real-time, large-scale, and varied public opinion data.

The rapid expansion of social media platforms such as Twitter has led to a massive volume of user-generated data, which serves as a valuable resource for informing organizational decision-making (Kamaswaran & Enigo, 2020). By examining this data, managers aim to improve customer relationships and foster business improvements (Zhao, Wen, Feng, Li, & Lin, 2020). Unstructured data dominates majority of the information exchanged across social media platforms (Gandomi & Haidari, 2015). The massive amounts of unstructured data available online poses significant challenges for manual analysis, making it difficult for customers and businesses to understand public sentiment towards products and services (Zhang, Tian, Fan, & Li, 2020; Gobi & Rathinavelu, 2019). To address these challenges, automating the collection and analysis processes becomes imperative (Chan & Thein, 2018). Natural Language Processing (NLP) techniques such as sentiment analysis, which leverage Artificial Intelligence (AI) and machine learning (Aguilar-Mareno, 2024), can be employed to effectively extract valuable insights from rich and dynamic unstructured data obtained from different platforms such as Twitter. Sentiment analysis is aimed at extracting individual's sentiments from textural data (Yadollahi et al., 2017). It has moved beyond academic research to become a valuable tool for businesses seeking to understand customer perspectives and demands in real time. Leveraging unstructured data obtained from social media enables organizations to make informed decisions, improve products and services, as well as forecast market trends and dynamics (Sathyan et al., 2021; Kim, Lee and Assar, 2022). However, a single sentence or documents can convey multiple or conflicting viewpoints on disparate subjects. To address the limitations of traditional sentiment analysis which typically focuses on overall sentiment of text or sentence, Aspect-Based Sentiment Analysis (ABSA) has emerged as a more fine-grained approach. ABSA offers a more nuanced analysis by identifying sentiments towards specific aspects within text (Schouten & Frasincar, 2015). Aspect Category Sentiment Analysis (ACSA), a core component of ABSA, focuses on identifying and categorizing multiple aspect categories and determining their corresponding sentiments within a sentence (Zhou & Law, 2022). This technique will be utilized in this study to identify and categorize multiple aspects and categories within tweets about McDonald's, along with their associated sentiments.

1.1 Motivation

Highly competitive and ever-growing fast-food market combined with the rapid evolution of digital communication necessitates sophisticated analytical tools to capture consumer sentiment. This study leverages advanced ABSA techniques to identify consumer sentiments towards specific categories and aspects associated with McDonald's.

McDonald's is recognized for its exceptional market share and brand recognition in the fast-food industry (Kee et al., 2021). The company is a global food service giant which serves approximately 70 million customers daily through its vast network of nearly 35,000 locations (Mulyo, 2023) in over 100 countries, employing approximately 2 million people globally (Njihia, 2019). The company's competitive advantage lies not only in its loyal customer base, but its commitment to quality, consistency, and standardization (Edeh et al., 2024). McDonald's established itself as the most valuable fast-food brand globally, with a brand value reaching $ 33.8 billion in 2020 (Branddirectory, 2020). According to Technomic's 2020 rankings, McDonald's enduring dominance in the fast-food industry was solidified in that year (Technomic, 2020). Furthermore, it was voted America's most liked restaurant in 2016 (QSR, 2020; Anggara & Kaukab, 2024). Despite its historic market dominance, the company has recently faced challenges as indicated by key performance metrics. It is experiencing a downturn and decline in sales. As reported by CNN (Goldman, 2024), U.S. stores open for at least a year declined by 0.7% compared to the same period last year. Additionally, McDonald's global sales of comparable stores saw a 1% drop, marking the first decline in this indicator since late 2020 (Goldman, 2024). Consequently, McDonald's serves as an ideal case study for this research, which leverages ABSA to identify areas of concern, particularly those associated with negative sentiment in public tweets. On the other hand, conducting an ABSA Analysis of McDonald's presents a unique opportunity for large-scale sentiment analysis. As a global fast-food giant that continually adapts to industry trends, McDonald's offers a rich dataset for investigating complexities of consumer and brand perception.

1.2 Goals

The objective of this study is to develop and evaluate an advanced Aspect-Based Sentiment Analysis (ABSA) model capable of accurately identifying and classifying fine-grained sentiments, aspects, and categories within large-scale social media data. By applying this model to a large dataset of tweets about McDonald's, this study aims to uncover valuable insights into public perceptions, identifying both positive and negative sentiment drivers.

1.2.1. Model Development and Training

Aspect-based sentiment analysis (ABSA) has witnessed significant advancement in recent years. Zhang et al. (2023) developed the BERT-BiCNN, a hybrid model, which integrates BERT with bidirectional LSTM and CNN layers to enhance feature extraction. This model significantly outperformed traditional classification methods in classification tasks. Similarly, Zeberg et al. (2022) demonstrated the efficacy of BERT-BiLSTM architecture for predicting mental health from social media data, highlighting the potential benefits of integrating deep learning models. Wang et al. (2021) introduced BERT-SAN, an extension of BERT integrating with self-attention to capture aspect-related information. In a related study, Zeberga and Gebremariam (2022) addressed the challenge of class imbalance in multi-label aspect categorization leveraging SMOTE and ensemble learning. Nourbakhsh et al. (2022) also employed SMOTE to enhance classification performance for minority classes.

Building upon the work of Zhang et al. (2023), Zeberg et al. (2022) and Wang et al. (2021), who showed the effectiveness of hybrid models that integrate BERT with traditional neural network architectures, our proposed model extends these approaches. The models proposed by them highlighted the potential of integrating BERT with other neural network architectures for improved feature extraction and aspect-related information. Our model builds on these insights by combining a BiLSTM layer to capture sequential dependencies with a transformer encoder for nuanced contextual understanding. To address the issue of imbalanced datasets, as identified by Zeberga and Gebremariam (2022) and Nourbakhsh et al. (2022), we employed SMOTE oversampling technique to ensure balanced class representation. By combining these advanced techniques and elements, our model aims to outperform existing ABSA models.

1.3 Research Questions

To achieve the above-mentioned research objectives, the following research questions are addressed:

1. How can insights from Aspect-Based Sentiment Analysis (ABSA) be utilized to inform McDonald's business strategies?

2. How does the integration of SMOTE and the enhanced multi-task BERT architecture improve the accuracy and robustness of the aspect-based sentiment analysis model for tweets about McDonald's?
3. Which aspects in negative tweets about McDonald's are most frequently associated with negative sentiment, and how these aspects vary across different categories?

1.4 Contributions

The research paper makes the following contributions:

1.4.1 Theoretical Contributions

- **Innovative Model Design:** The integration of BERT, BiLSTM, and Transformer layers into a unified model, enhancing the model's ability to capture complex sentence structures and contextual nuances.
- **Advanced Insights into Sentiments, Aspect Relationships:** By concurrent analysis of sentiments, aspects and categories, this study provides insights into how these elements interplay within text, contributing to a richer and more detailed understanding of sentiment expression.

1.4.2 Practical Implications

- **Enhanced Business Decision Making:** Implementing a comprehensive ABSA analysis of McDonald's, a global food service giant with considerable social media presence, this study offers actionable insights into public sentiment associated with specific product features and enables businesses to make data-driven and informed decisions in areas such as marketing, product development and enhancement as well as customer service and engagement.
- **Improved Customer Understanding:** By identifying and analyzing underlying themes in customer feedback through concurrent analysis of categories, aspects and sentiments this study presents valuable insights into customer needs and preferences which in turn allows businesses to tailor their offerings accordingly.

1.5 Structure of the thesis

This thesis is structured as follows:

- Chapter 2 reviews existing literature on sentiment analysis and Aspect-Based Sentiment Analysis emphasizing their application in social media monitoring

- Chapter 3 Outlines the research methods, including data collection, tools and models used and the procedures of data analysis.
- Chapter 4 presents the results of model performance and findings from model applied to real-word tweets about McDonald’s
- Chapter 5 discusses the implications of the results, relates them to the research questions, and address study limitations

2. Literature Review

In this chapter, some background literature on the research areas related to the thesis topic will be provided. Section 2.1 explains the significance of social media in academic research and business world. Section 2.2 provides the fundamentals of machine learning, covering key concepts and techniques that are essential for comprehending subsequent discussion. Section 2.3 details the development of sentiment analysis systems. It mentions the limitations inherent in these systems and how these challenges can be addressed by aspect-based sentiment analysis (ABSA). Additionally, a brief overview of previous research conducted in this area will be provided. Section 2.4 delves deeply into Aspect-Based Sentiment Analysis (ABSA). This section explores the wide-ranging applications of ABSA in various domains. It will then shed light on the architectural framework of ABSA models. Furthermore, this section will review previous research conducted in ABSA, focusing on the state-of-the-art systems, challenges and limitations within the field. Finally, section 2.5 explores SMOTE (Synthetic Minority Over-sampling Technique), a method used to address class imbalance in datasets. It discusses the technique's effectiveness in generating synthetic data points for minority class and its integration with various machine learning architectures. Finally, section 2.6 covers evaluation metrics used to assess the performance of aspect-based sentiment analysis (ABSA) models.

2.1 Social Media

The advent and exponential growth of social media platforms have not only revolutionized the nature of online participation but have also become intricately woven into the fabric of our daily lives. These platforms now serve as primary channel of accessing information, entertainment, engagement and building relations (Avalle et al., 2024) globally and have changed how people live (Fong Boh et al., 2023).

Media is referred to as a collection of internet-based applications that utilize the "ideological and technological foundations of Web 2.0", enabling the creation and distribution of user-generated content. User Generated Content (UGC) is considered as the all the ways in which people utilize social media. In other words, it is referred to as different types of "media content" that are generated by "end-users" and are publicly accessible (Kaplan & Heanlein, 2010, p. 61). According to the Organization for Economic Cooperation and Development (OECD, 2007), for content to be considered as UGC, it must possess three characteristics: first, it needs to be published on a publicly accessible website or a social media platform; second, it should involve a certain amount of effort in creation; Finally, the creation should take place outside of regular scope of someone's employment (Vickery et al., 2007).

A social network is a dynamic web of connected social units (Smith & Doe, 2011) involving individuals or organizations, brought together through shared interests or experiences on an online platform that facilitates interaction. Based on a growing body of research, social media has become an integral part of daily lives of its users (Okazaki, 2009; Peng et al., 2004; Seo & Park, 2018). The ongoing digital revolution has reshaped the media landscape. Traditional media is no longer a one-way communication. Consumers are empowered to participate in conversations and influence direction of news coverage and cycle. This shift has made traditional methods of information search and news spread increasingly outdated Chung & Koo, 2015) and has shaped new avenues for social interaction and information acquisition.

Social media has become an undeniable phenomenon in our world. According to Qusnul Saputri et al. (2024), more than half of the global population (out of approximately 8 billion in 2023) used social media. As of 2024, Facebook, the world's largest social media platform, boasts 3.065 billion monthly active users. Other major players such as YouTube (2.054 billion), Instagram (2 billion), WhatsApp (2 billion) and Twitter (335.7 million) cater to diverse user preference (Statista, 2024).

The proliferation of data and information fueled by the information revolution has led to emergence of new economies characterized by novel landscapes (Serrat, 2017). The ubiquitous rise of "digital communication technologies" such as the internet and mobile phones, has opened doors to analyzing human behavior with an unprecedented level of detail. A diverse range of online platforms including internet forums, blogs and social media networks generate data in real-time, exhibiting second-by-second variation (Steinert-Threlkeld, 2018, p. 1). Social media platforms have served as a pivotal marketing tool, providing companies and brands with a unique approach to engage with their audience (Seo & Park, 2018). These platforms exemplify interaction among millions of people due to an extensive amount of user-generated content, real-time information dissemination and pervasive network infrastructure (Gadek et al., 2018). The rise of social media and e-commerce platforms has transformed customer feedback into a rich and invaluable resource for assessing satisfaction with products or services. Online comments and reviews offer unprecedented insights into customer sentiment, preference, and experiences (Moghadam, 2015). The success of social media networks heavily depends on the level of user engagement in exchanging information (Wang et al., 2010).

Unstructured data constitutes a vast majority of the information transmitted across social networks (Gandomi & Haider, 2015). Content come in a variety of formats with interaction predominantly occurring in natural language abundant with slang, abbreviations, and emotions. This poses a significant challenge for businesses and conventional data analysis tools (Shmueli et al., 2017). However, this challenge also presents a unique opportunity for gaining deeper insights. Driven by the potential of deeper understanding, businesses and researchers aim to leverage unstructured data to gain deeper insight into evolving dynamics of society and the market (Cano-Marin et al., 2023). This is fueled by concurrent rapid evolution of Artificial Intelligence (AI)-based technologies, continuous advancements in computational power (Duan et al., 2019) and cloud computing facilitating the analysis of big data (Moreno & Redondo, 2016). By leveraging Natural Language Processing (NLP), which is a subfield of AI, researchers and businesses can gain valuable insights within this unstructured data.

This study focuses on Twitter, a social media network boasting over 300 million active accounts from almost every country generating more than 300,000 tweets per minute (Domo, n.d). Additionally, according to internal Tweeter data, 1.7 million people join Twitter everyday (@XDATA, 2024). Twitter is used by wide range of people from political figures, CEOs to normal citizens. Users are evenly distributed across urban, suburban, and rural areas, with equal representation of both genders. All these people and messages mean that Twitter mirrors various populations eliminating the need for large teams of researchers to analyze these segments simultaneously (Steinert-Threlkeld, 2018). Twitter's publicly available data, global reach with users from almost every country, extensive user base, and reputation as a general-purpose platform with relative openness (Steinert-Threlkeld, 2018) as well as its geographically and demographically balanced user base makes it a rich resource for researchers studying a wide range of topics (Steinert-Threlkeld, 2018, p. 3) and therefore, positions it as particularly well-suited for this study. Due to these characteristics, all significant events are documented on Twitter, enabling researchers to track emerging trends that might predict future developments (Steinert-Threlkeld, 2018). Compared to traditional media, content and news on Twitter circulate at a significantly faster pace, due to its inherent real-time nature and volume of user-generated content often characterized by a tendency towards more negativity and outrage (Brannon & Ray, 2024). This rapid circulation enables researchers to capture trends and collective sentiments with unparalleled details. Unstructured data obtained from Twitter in real-time is a goldmine of potential business insights and competitive advantages. By effectively translating this data into business insights and competitive advantages, companies such as McDonald's can achieve important improvements across several critical domains including "effective decision-making process", "identification of customer requirements", and "boosting productivity" (Blumbertg & Atr, 2003; Niu et al., 2021 Cano-Marin, 2023).

2.2 Machine Learning

Machine Learning is a branch of Artificial Intelligence (AI) (Kumar et al., 2021) which utilizes algorithms to allow computers to make decision by leveraging and learning from data. It involves various methods designed to identify patters in data which leads to better decision-making process (Ngai & Wu, 2022). ML can make predictions by learning without explicitly being programmed for each task (Samuel, 1959; Mahesh, 2020). It is one of the key technologies in the fourth industrial revolution (Sarker, 2021, p. 1) and has different applications in diverse fields such healthcare, finance (Yazdani et al., 2018), marketing (Chen et al., 2017), customer service (Jain & Kumar, 2020) manufacturing (Rude et al., 2015), transportation (Tizghadam et al., 2019) and many other, revolutionizing data analysis and utilization. Machine learning is a robust tool that can automate the data analysis task. By mining vast datasets businesses can leverage machine learning to uncover patterns in customer behavior (Cui et al., 2016). Machine learning can be categorized into four main types: supervised, unsupervised, semi-supervised and reinforcement learning (Mohammed et al., 2016).

In reinforcement learning, systems learn to improve at a task repeated attempts and feedback over time (Sutton & Barto, 1998). By receiving positive or negative feedback on their performance, reinforcement learning algorithm can self-adjust and attempt the task again with new data or previously encountered data (Sutton & Barto, 2018).

In supervised learning, the model is trained on a labeled dataset. The objective is to develop an "artificial system" with capability to learn the mapping from feature inputs to output labels (Liu & Wu, 2012). The main drawback of learning is the need for labeled data which can be time-consuming, expensive and labor intensive. Commonly used supervised learning techniques encompass traditional epidemiological methods such as linear and logistic regression, along with widely used machine learning algorithms such as decision tree and support vector machines. Supervised machine learning algorithms can be divided into classification and regression tsks based on the nature of response variable. Classification predicts categorical outcomes, while regression focuses on predicting continuous outcomes (Bi et al., 2019).

In unsupervised learning, the algorithm learns to identify hidden patterns and groupings in data without predefined outcomes for "correct answers" (Duda et al., p.517). It is a field within machine learning which learns from unlabeled data to uncover hidden patterns or structures. Unsupervised learning has similar objectives and frameworks to statistical approaches that seek to identify hidden subgroups or patterns such as latent variables or classes (Bartholomew et al., 2011; Bi et al., 2019). Clustering and Dimensionality Reduction are two major techniques and powerful approaches to unsupervised learning. Clustering algorithms, such as k-means and exception-maximization with Gaussian mixture models, are widely used unsupervised learning approaches that group observations based on similar data characteristics (Bishop, 2006; Hennig, 2015; Bi et al., 2019).

Semisupervised learning involves combining labeled and unlabeled data to train models. Since labeling data can be expensive and time-consuming for large datasets, semisupervised learning leverages small volume of labeled data with a large amount of unlabeled data to improve model performance (Bi et al., 2019). Studies have shown that unlabeled data can improve classifier accuracy when appropriate models are selected (Zhu et al., 2009).

Machine learning algorithms, regardless of whether they are supervised or unsupervised, can be classified as either discriminative or generative (Vapnik, 19698; Ng & Jordan, 2002). Discriminative algorithms concentrate on modeling the conditional probability of an outcome based on input data. Modern machine learning classifiers, such as logistic regression, Support Vector

Machine (SVM), supervised feedforward deep neural networks, nearest neighbors and conditional random fields are primarily focus on discriminative classification, which involves modeling the decision boundary between classes directly from training data (Harshvardhan, 2020). Logistic Regression, SVM, and Random Forest are among the most commonly used discriminative models in machine learning, valued for their effectiveness, interpretability, and ease of implementation. Linear regression is a powerful supervised learning algorithm which is used to predict value of dependent continuous variables by establishing a linear relationship between dependent target variable and one or more independent variables (features). Logistic regression is a supervised machine learning algorithm which estimates the probability of an event. It is used for classification problems to "classify an observation into one of the two classes" or into "one of many classes" (Jurafsky & Martin, 2024, Chapter 5). SVMs are powerful supervised learning models used for classification and regression tasks. They work by finding the optimal line or hyperplane that best classifies the data into different classes by maximizing the margin between each class in a multi-dimensional space (Mahesh, 2020). Random forest is a commonly used supervised learning algorithm. It is an ensemble of decision trees (classifiers) which are popular models for splitting the data based on feature to arrive at a single prediction. During the process, multiple decision trees are created on random subsets of data. A single result is predicted by averaging the results obtained from several decision trees which in turn improves accuracy and controls overfitting.

Generative algorithms differ from discriminative algorithms in that they compute conditional probability of an outcome indirectly. They start by modeling the joint probability distribution, which encompasses all possible combinations of input and output variables (Bi et al., 2019). Naive Bayes, as notable example of a generative model, is a type of generative learning algorithm which is based on Bayes theorem with the naive assumption of the occurrence of a feature independent of the other features. It is commonly used for textual classification on high-dimensional datasets (Raschka, 2014).

2.2.1 Neural Networks

Neural networks also called an Artificial Neural Networks (ANNs) has emerged as a cornerstone of supervised machine learning. they are "inspired by cognitive science" and human brain structure (Xu et al., 2021, p. 2). Neural networks also called deep learning consist of layers of interconnected processing nodes, or artificial neurons. These include an input layer, multiple hidden layers and an output layer (Sarker, 2021).

Each node or neuron in a layer receives input data from neurons in the previous layer, manipulates this input by adjusting parameters called weights, applies an activation function, and sends the output to the next layer. Deep learning uses deep neural networks to recognize and learn complex patterns and abstract representations from data (LeCun et al., 2015).

Neural networks depend on training data to learn and improve their performance. Each node connects to others and training neural network involves updating weights of the nodes. the weight is then adjusted to minimize the error between the network's predictions and actual values of the output data. This process is called Back-Propagation which is the most widely used supervised learning algorithm (Sapna et al., 2012). This algorithm computes the gradient of the loss function concerning each weight using the chain rule which leads to automatic differentiation and efficient computation of the gradients for all weights. Gradient descent is an iterative optimization algorithm with several variants such as Stochastic Gradient Descent (SGD), batch gradient descent, mini-batch gradient and momentum gradient descent. It is utilized to update the weights (Goodfellow, Bengio, & Courville, 2016).

2.2.2 Deep Learning

Deep Learning (DL) is a branch of machine learning which was introduced by Hinton et al. in 2006 (Hinton, Osindero, & Teh, 2006). It was based on the concept of artificial neural network (ANN). Since then, deep learning attracted significant attention and was referred to as "new-generation neural networks" because it utilized neural networks with multiple layers (Karhunen, Raiko, & Cho, 2015). While it might be time-consuming to initially train a deep learning model for large datasets due to many parameters, it can take shorter during usage due to faster processing. Deep learning algorithms utilize artificial neural networks with many hidden layers which enables them to extract "high-level features" from raw input data (Alpaydin, 2020; Deng & Yu, 2014).

Deep learning is not new and has existed for a long time. However, the unprecedented volume of data, the deployment of deeply layered neural networks, and the utilization of GPUs coincided to drive the explosive growth of deep learning. Deep learning models are developed depending on specific types of tasks.

2.2.2.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a specific type of deep learning structure which are particularly effective for tasks involving images and videos. They are inspired by the human visual system. CNNs also have opened doors to many other applications such as image and video classification, object detection, facial recognition, medical image analysis and segmentation. CNNs are made of four layers including convolutional layers, pooling layers, Rectified Linear Unit, and fully connected layers (Alwani et al., 2016; Song et al., 2019).

2.2.2.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a specific type of deep learning model which are particularly well-suited for processing time-series or sequential data (Weerakody et al., 2021) such as words and sentences. Therefore, they are suitable for tasks such as Natural Language Processing

(NLP), speech recognition, language translation, time series forecasting (Tarwani & Edem, 2017). Practical applications of RNNs are Google Translate and Siri (Johri et al., 2021). Like CNNS, RNNs learn from labeled data. RNNS have an internal memory which enables them to store information about prior inputs, take them to influencing the processing of current input and output. Unlike traditional deep neural networks, RNNs do not consider inputs and outputs independent of each other; in fact, the output or RNNs are influenced by prior elements (Graves et al., 2013; Lipton et al., 2015).

2.2.2.2.1 Long-Short Term Memory (LSTM)

RNNs have traditionally encountered challenges in learning long-term dependencies (Siami-Namini et sl., 2019) due to vanishing gradients. LSTMs is an improvement of RNN which have been developed upon RNNs by Schmidhuber et al. (1997) to address the problem of vanishing gradients in long sequences (Lu et al., 2021). LSTMs and Gated Recurrent Units (GPUs) are variants of RNNS designed to overcome the limitations of RNNs using gating mechanisms to control the information flow within the network (Choi & Lee, 2023). Unlike standard RNNs which typically use a single, simple repeating module typically involving a tahn layer, LSTMs introduce a more intricate architecture featuring three multiplicative units (forget, input, and output) and a memory cell. This enhanced structure, which includes four distinct modules, is designed to effectively learn and retain long-term dependencies in sequential data (Borovkova & Tsiamas, 2019; Livieris et al., 2020; An et al., 2020). Bidirectional LSTM (BiLSTM) process input sequences in bout forward and backward directions. To construct BiLSTM network, the LSTM neurons are split into two groups: one processing the forward states, while the other processing the backward states (Schuster & Paliwal, 1997). Figure 1 illustrates the architectures of LSTM and BiLSTM networks. The bidirectional nature of BiLSTM network allows them to process the input data from both the past and future time frames. This contrasts with standard LSTM, which only process information form past, potentially causing delays in capering and understanding future context.

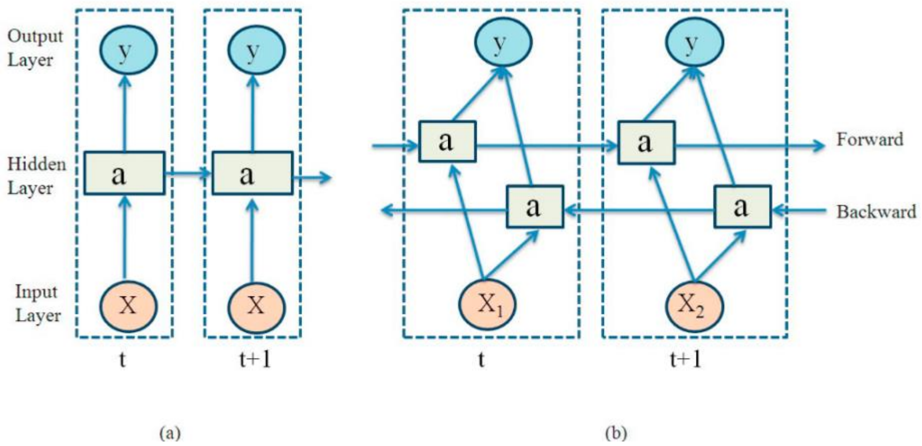

Figure 1: Architectures of (a) LSTM and (b) BiLSTM network (Mahadevaswamy & Swathi, 2023, p. 49)

2.2.2.3 Generative Adversarial Networks (GANS)

Generative Adversarial Networks (GANs) is a powerful deep learning architecture. It was first introduced by Goodfellow and his colleagues in 2014. It has revolutionized generative modeling. It is called adversarial because it consists of two networks, a generator and a discriminator which compete to produce more authentic data. They are iteratively trained through a process called adversarial training. The generator network is responsible for generating new data samples that are similar to training data. Throughout this process, random noise vectors are taken as input and are converted to data samples. Using a probability value, the discriminator network determines whether the produced data belongs to training dataset. The process continues and enhanced versions of fake data values are produced until the generated data is indistinguishable from real data (Zhang et al., 2021).

2.2.2.4. Graph-Convolutional networks (GCNs)

Traditional classification methods often overlooked data interdependencies, which adversely effected classification model performance (Shen et al., 2020). To address this limitation, representing data as a graph has been proposed, which enabled explicit modeling of complex relationships between data points (Zhu et al., 2019; Kang, Pan, Hoi, & Xu, 2020). While CNNs have excelled in processing grid-like data, their effectiveness is limited when applied to graph-structure data due to the challenges associated with convolution and filtering in non-Euclidean spaces (Hammond, et al., 2011; Henaff et al., 2015; Hu, Zhu, Zhu, & Gan, 2019; Kang et al., 2020). To address these challenges, Graph Convolutional Networks (GCNs) were proposed by Kipf and Welling (2017), leveraging innovative convolutional kernels to effectively process the irregular structure of graph-based data (Battaglia et al., 2018). GCNs have proven to be a leading method for a wide range of applications, such as Aspect-Level Sentiment Analysis (ALSA), by effectively capturing and modeling data interdependencies (Phan et al., 2022).

GCN-based methods utilize deep learning algorithms (Wu et al., 2020) to process graph-structured data (Zhou et al., 2020) to implement various tasks that require models capable of capturing complex dependencies embedded in textual data (Khemani et al., 2024). By iteratively aggregating and transforming information across nods in graph, GCNs can effectively predict features associated with specific nodes, their connections, or the entire graph (Qin et al., 2021). This adaptability to diverse graph structures allows CGNs to capture complex relationships among words, aspects and sentiments within textual datasets (Abadal et al., 2021). These properties enable GCNs to excel in a wide range of fields. In particular, particularly in NLP tasks (Bastings et al., 2017; Ma et al., 2021; Liao et al., 2021) such as text classification (Huang et l., 2019) and relation extraction (Zhang et al., 2018). Additionally, GCNs have demonstrated promising results in computer vision applications (Johnson, 2018; Wang et al., 2019), and recommender systems (Van den Berg, et al., 2017).

2.2.2.5 Transformer-Based Models

The emergence of transformer architectures, exemplified by models such as Bidirectional Encoder Representations from Transformers (BERT), which excel in aspect-based sentiment analysis by effectively capturing long-range dependencies and contextual nuances. The fine-tuning of pre-trained transformer models for ABSA has become a standard practice, leveraging their knowledge gained from massive amounts of pre-training on diverse text corpora (Chavez et al., 2023). Transformers leverage a self-attention mechanism to capture complex dependencies between words within a text. Unlike RNNs, which process sequences sequentially, transformers process all words simultaneously in parallel. This enables transformers to effectively understand relationships and contextual nuances across the entire sequence. The self-attention mechanism can be mathematically represented as scaled dot-product attention formula:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

In the self-attention mechanism of transformers, Q , K and V denote the metrics of query, key, and value vectors, respectively. The parameter d_k represents the dimensionality of the key vectors.

Figure 2 illustrates the architecture of transformer, which consists of an encoder and a decoder. The encoder maps a sequence of input symbols $(x_1, \ldots, x_n)$ into a sequence of continuous representations (z = $(z_1, \ldots, z_n)$). The decoder then creates the output symbol sequence $(y_1, \ldots, y_m)$ incrementally, leveraging the encoded representations z. The figure illustrates key components such as input and output embeddings, positional encoding, multi-head attention, feed-forward neural networks, and the final linear and softmax layers (vaswani et al., 2017).

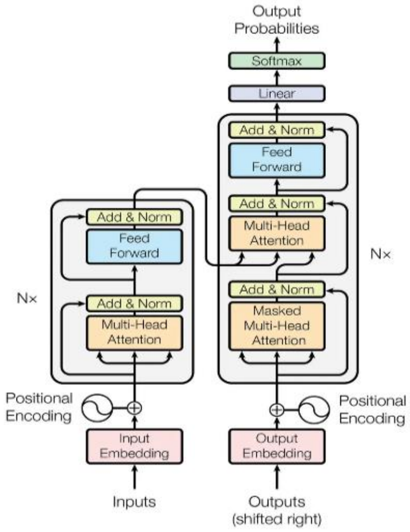

Figure 2: Transformer architecture (vaswani et al., 2017)

In the context of ABSA, the transformer model's encoder processes both the textual data, such as tweets, reviews, so on and the aspect as input, converting them into high-dimensional representations. The decoder subsequently takes these representations to create the desired output, such as sentiment polarity of aspect. The self-attention mechanisms embedded within the transformer architecture enables both encoder and decoder to capture global dependencies across the text, facilitating efficient information flow.

2.2.2.5.1 BERT

BERT, a highly sophisticated transformer-based language model introduced by Delving et al. (2018), has established a new benchmark in NLP. Using attention-mechanisms, BERT processes entire text sequences in parallel, producing rich sentence-level representations that capture complex semantic relationships between words. Unlike traditional word embedding methods, BERT's bidirectional approach (Tenney et al., 2019) considers both preceding and succeeding contexts, leading to a deep and nuanced contextual understanding and produce rich vector representations. This is achieved through pre-training on extensive text corpora utilizing unsupervised techniques such as Next Sentence Prediction and Masked Language Modeling. This approach helps BERT learn the contextual relationships between words (Delvin et al., 2019), enabling it to excel in various tasks such as sentiment analysis, text classification, question answering, and machine translation (Mughal et al., 2024).

Given Bert's superior performance in NLP tasks compared to general neural network models, several research have explored hybrid models that combine BERT with other architectures to further enhance results (Mewada & Dewang, 2022). Talaat (2023) developed hybrid models that combines the strength of BERT with Bidirectional Long Short-Terms Memory (BiLSTM) and Bidirectional Gated Recurrent Unit (BiGRU) layers for sentiment analysis. The results indicate that the hybrid models, particularly those using BiGRU layers, performed better than standalone BERT models. Pandey (2023) propose a hybrid model that combines the strengths of BERT with LSTM for sarcasm detection. This approach effectively leverages the capabilities of each component where BERT generates word embeddings for the text, and these embeddings are processed by LSTM network to classify the text as sarcastic and non-sarcastic. The results demonstrate that BERT-LSTM model significantly outperforms traditional machine learning models and other deep learning models. Zhang et al. (2023) improved BERT model for classification by bidirectional LSTM-CNN deep model (BERT-BiCNN) to address the challenges of extracting meaningful features from textual data. BERT-BiCNN model outperformed several baseline models including traditional BERT and other deep learning structures such as CNN and LSTM, achieving higher precision, recall, and F-1 scores. Similarly, a study implemented by Zebega et al. (2022) aimed to develop a model to predict mental issues from social medial posts by combining two deep learning models, BERT (Bidirectional Encoder Representations from Transformers) and Bi-LSTM (Bidirectional Long Short-Term Memory). The paper claimed that the proposed hybrid model achieved an accuracy of 98% in predicting mental health issues from social media posts. The results indicated that the combination of BERT and Bi-LSTM significantly improved the model's performance compared to using each model individually. Wang et al. (2021) proposed a novel model called BERT-SAN (BERT self-Attention Network) that extends the pre-trained BERT model to handle two correlated subtasks: Aspect Relatedness Prediction and Aspect-Based Sentiment Analysis. The BERT-SAN enhances the BERT architecture by adding a task-specific self-attention network (SAN) layer on top of the BERT model. This additional layer is designed to capture the relationship between words in a sentence, with particular attention to how they relate to a given aspect.

2.3 Sentiment Analysis

Sentiment Analysis which is sophisticated, widely used and fundamental NLP technique (Wang et al., 2018) is aimed at extracting individual's sentiments and perspectives from textual data (Yadollahi et al., 2017). As indexed in databases such as Elsevier's Science Direct, IEEE Xplore Digital Library, Springer Link, ACM Digital Library and Wiley Online Library, the number of research papers focusing on sentiment analysis within social networks has grown exponentially with a year-on-year increase of 34% (Rodríguez-Ibáñez et al., 2023). Additionally, sentiment analysis has moved beyond academic research to become a valuable tool for organizations and businesses. Social media platforms now serve as rich sources of data for understanding and managing public perception through effective marketing and communication strategies (Rodríguez-Ibáñez et al., 2023). From evaluating public opinion on products (Geetha & Renuka, 2021) and services (Bensoltane & Zaki, 2022) to monitoring brand reputation and analyzing market trends through social media data (Bonifazi et al., 2022; Patil & Kolhe, 2022), sentiment analysis of social media data has become a powerful tool for understanding customer opinions (Phan et al., 2023), particularly customers' sentiments towards targeted categories (Nasim & Haider, 2017). As a result, sentiment analysis has proven to be an essential tool across industries. It has been widely applied to customer reviews (Yu et al., 2017; Amplayo et al., 2018; Dou, 2017; Wu et al., 2018) and has proven to be a valuable strategy for enhancing market performance and customer satisfaction (Salinca, 2017). Sentiment analysis enables businesses to gain valuable insights into public opinion, brand perception and market trends from various sources, including social media, news articles, customer reviews and surveys. Furthermore, sentiment analysis, a valuable tool for strategic planning, provides insights into product innovation, marketing strategies, and customer service enhancement. Additionally, it assists to protect brand reputation by swiftly responding to negative comments which in turn leads to cultivating a positive brand image (Huang et al., 2023).

Nassirtoussi et al. (2014) examined the application of sentiment analysis to market prediction. Rambocas and Pacheco (2018) conducted a study of sentiment analysis in marketing research by focusing on three key aspects: the sampling design, unit of analysis and statistical analysis. Cheng et al. (2022) provided a systematic overview of various techniques including semantic, sentiment and event extraction employed in stock forecasting using sentiment analysis.

Numerous studies have explored sentiment analysis within text, with a particular focus on social media platforms. For example, Yue et al. (2019) conducted a comprehensive survey of numerous techniques and approaches within social media domain. Kumar & Garg (2020) offered a comprehensive overview of sentiment analysis on Twitter employing a natural language processing technique. Other relevant research includes Singh (2020) on sentiment polarity in Twitter, Chandio & Sah (2020) on predicting opinions about Brexit, and Kraaijeveld & Smedt (2020) on forecasting cryptocurrency price returns.

Traditional approaches of sentiment analysis typically rely on feature engineering which involves transforming raw data into relevant information. These features often encompass n-grams (word sequences), analytic features and sentiment-specific terms. Prior to the development of advanced machine learning, researchers predominantly relied on manual feature engineering for sentiment analysis (Cui et al., 2023). For instance, Feldman (2013) explored methods for extracting target entities from indirect opinion. Asghar et al. (2014) reviewed different NLP methods for feature extraction. Additionally, Taboada (2016) provided a linguistic perspective on sentiment features, analyzing the characteristics of words, phrases and sentence structures. Traditional sentiment analysis approaches have demonstrated effective results and strong performance through careful feature engineering (Habimana et al., 2020). Common features utilized in these methods include part-of-speech (POS) tags (Pang et al., 2002) word position (Pang et al., 2002), opinion words and sentences (Kalchbrenner et al., 2014; Taboada et al., 2011; Akter & Aziz, 2016; Diamantini et al., 2016), negation handling (Diamantini et al., 2016), term frequency (Mukherjee & Joshi, 2014), and syntactic dependencies (Perikos & Hatzilygeroundis, 2017).

The process of manual feature engineering was time-consuming and often faced scalability limitations (Khurana et al., 2016), posing challenges for its application to extensive datasets. The advent of machine learning enabled the automated extraction of complex features. Using these engineered features, simple machine learning algorithms such as Support Vector Machine (SVM) and Naive Bayes were typically employed to classify sentiments (Kiritchenko et al., 2014). Many papers have focused on applying machine learning techniques to sentiment analysis (SA). Sagnika et al. (2020) conducted a multilingual sentiment analysis approach focusing on machine learning, while Mehta and Pandya (2020) summarized studies incorporating both machine learning and lexicon analysis. Shathik and Prasad (2020) outlined the most used machine learning techniques for SA. Umar et al. (2021) investigated the impact of levels of sentiment classification and data sources on various supervised machine learning techniques, including Naive Bayes, Maximum Entropy and SVM, as well as lexicon-based approaches. However, these traditional approaches encounter two primary limitations. Firstly, their performance is heavily influenced by the precision of hand-crafted features. Secondly, they struggle to discern intricate sematic dependencies between aspects and their contextual elements (Huang et al., 2023).

Deep neural networks have emerged in response to the limitations of traditional machine learning methods. They have revolutionized the field of sentiment analysis, achieving remarkable success by demonstrating significant advancements in accuracy and robustness (Chen et al., 2020). This have led to widespread adoption of Recurrent Neural Networks (RNNs) (Yu et al., 2019; Do, 2018), Convolutional Neural Networks (CNNs) (Li et al., 2022; Sadr et al., 2021; Wang et al., 2021) and Transformers (Lin et al., 2022) for sentiment analysis and Aspect-Based Sentiment Analysis (ABSA).

Numerous studies have explored deep learning methods. Prabha and Srikanth (2019) conducted an in-depth analysis of various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) as applied to sentence-level and aspect/object-level sentiment analysis. Their study explored the advantages, limitations, and performance metrics of these models across different application contexts. Ain et al. (2017) employed deep learning models including Deep Neural Network (DNN), CNN and Deep Belief Network (DBN) to address a range of sentiment analysis challenges, such as sentiment classification, cross-lingual sentiment analysis, and product review analysis. Habimana et al. (2020) implemented a comparative analysis of various deep learning techniques on specific datasets and proposed that performance enhancement could be achieved through integration of advanced models such as Bidirectional Encoder Representation from Transformers (BERT), "sentiment-specific word embedding models", cognitive-based attention mechanisms, "common sense knowledge", "reinforcement learning" and generative adversarial networks (GANs).

Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) stand out as prominent deep learning architectures (Huang et al., 2022; Zeng et al., 2022) which typically employ word embeddings as input (Rodríguez-Ibáñez et al., 2023). Although RNNs were initially employed for sentiment classification (Dong et al., 2014) and possess substantial computational capacity due to their Turing completeness and capability to process sequential data, they face the challenge of exploding or vanishing gradient problem which restrict their application to long sequences with long-term dependencies (Fernández et al., 2024). This led to the development of Long Short-Term Memory (LSTM) networks which have become the foundation for many aspect-based level sentiment classification methods. Notable examples in this area include Target Dependent LSTM models (TD-LSTM and TW-LSTM) introduced by Tang et al. (2015) and the Memory Network (MemNet) proposed by Tang et al. (2016). Building on these advancements, Xue and Li (2018) further advanced the field with the Gated Convolutional Network with Aspect Embeddings (GCAE).

Attention mechanism have significantly improved sentiment classification performance. Wang et al. (2016) proposed the integration of attention into LSTM networks with their ATAE-LSTM model. Yang et al. (2017) further advanced this approach by introducing multiple attention methods tailored for target-dependent sentiment analysis. Xu et al. (2020) proposed a multi-attention network to enhance sentiment classification within social networking. Shuang et al. (2019) integrated attention and positional information of context words employing double LSTMs. Subsequently, a similar strategy was adopted by Zhou et al. (2020) and Shuang et al. (2021) to improve model accuracy.

Several research papers have explored sentiment analysis in non-English languages. Studies have been implemented in Arabic (Al-Ayyoub et al., 2019; Boudad et al., 2018; Nassif et al., 2021; Queslati et al., 2020), Chinese (Peng et al., 2017), Spanish (Angel et al., 2021), Urdu (Khattak et al., 2021), and Portuguese (Pereira, 2021),

Sentiment analysis aims to capture and identify emotional expressions withing text. Main dimensions of sentiment analysis include polarity, granularity, and target. Polarity is the orientation of text, typically categorized as positive, neutral, and negative. Granularity indicates the level of detail in sentiment analysis which can be document-level, sentence-level and aspect-level. Document-level sentiment examines the overall emotional tone of an entire text, sentence-level sentiment assesses the sentiment expressed within individual sentences, and aspect-level sentiment focuses on sentiment towards specific components or features of an entity. Target refers to the subject of sentiment and is categorized as targeted or untargeted sentiment. Targeted sentiment analyzes opinions directed towards specific entities, topics, or aspects, while untargeted sentiment examines overall emotional tone of the text without emphasizing particular elements (Phan et al., 2024).

Sentiment analysis is primarily conducted at three granularities: document-level, sentence-level and aspect-level (Brauwers & Frasincar, 2023). In other words, the graduality of sentiment analysis can be tailored to suit specific needs, ranging from the overall sentiment of an entire document to sentiment expressed towards specific aspects within individual sentences (Liu, 2012; Liu, 2015; Pozzi et a., 2017; Habimana et al., 2020). Document-level sentiment analysis determines the overall sentiment of the entire documents as positive, neutral, or negative. Sentence-level sentiment analysis, on the other hand, determines whether individual sentences are subjective or objective. if subjective, whether the sentiments expressed are positive, neutral, or negative. While some studies suggest a correlation between subjective expressions and sentiment, it is important to note that objective expressions can also carry sentiment (Liu, 2010). Fundamentally, sentence-level sentiment analysis is like document-level analysis, but with a narrower focus on individual sentences (Liu, 2012). However, unlike the assumption of consistent sentiment in many existing sentiment analysis approaches, real-world text often exhibits dynamic sentiment shifts (Liu, 2010). Therefore, to effectively address these challenges, a detailed level of sentiment analysis is required (Mughal et al., 2024). Aspect-level sentiment analysis is a granular approach to examining sentiment within text (Liu 2012; Pontiki, 2015; Trisna & Jie, 2022). As a rapidly evolving field, it has gained significant attention (Brauwers & Frasincar, 2023) due to its ability to provide nuanced perspective by identifying specific aspect terms of an entity and determining sentiment polarity of each aspect (Zhao et al., 2023). An entity is district and indefinable object or concept that exists independently. It represents a variety of elements, including people, events, objects, organizations, products, or abstract concepts (Phan et al., 2024).

2.4 Aspect-Based Sentiment Analysis

The exponential growth in user-generated content has necessitated research in NLP leading to productive areas of research such as Aspect-Based Sentiment Analysis (ABSA). ABSA has emerged as a more fine-grained approach to sentiment analysis to address limitations of traditional methods which primarily focus on overall sentiment of a text (document-level) or sentence (sentence-level) (Liu, 2015). As a single sentence or document can convey multiple opinions on different subjects, ABSA offers a more nuanced analysis by identifying and examining sentiments toward specific aspects or entities within the text (Schouten & Frasincar, 2015). Aspects refer to the specific features and attributes mentioned within the text (Pang & Lee, 2008). In sentiment analysis, entities and aspects are core concepts. Entities are the subject of analysis which typically refer to concrete subjects such as products, services, people, events, or organizations (Liu, 2020), whereas aspects represent their specific features or attributes. Since aspects can exhibit varying degrees of detail, a hierarchical structure can effectively illustrate the relationship between entities and the relevant aspects. They can be structured as a tree-like model in which the entity serves as the root node, and the layers below representing more detailed aspects. Hu and Liu (2004) classify aspects into explicit and implicit forms. Explicit aspects are directly expressed in the text, while implicit aspects are inferred from the contextual knowledge which requires employing a deeper analysis.

ABSA primarily aims at identifying aspects and classifying sentiment (Truşcă & Fransincar, 2023). However, recent advancements in ABSA have evolved the classification of ABSA tasks. The SamEval 2014 workshop (Pontiki et al., 2014) proposed a framework for ABSA, outlining four distinct tasks: aspect term extraction, sentiment classification for each aspect term, aspect category detection, and sentiment classification for each aspect category. The SemEval 2015 and 2016 workshops (Pontiki et al., 2015, 2016) refined the framework introduced in 2014 by addressing overlaps in the four proposed tasks. They note that sentiment assigned to an aspect should generally align with the sentiment assigned to its category. As a result, these subsequent workshops consolidated the four tasks into three (Truşcă & Fransincar, 2023).

ABSA involves several key subtasks. These include Aspect Term Extraction (ATE), which identifies the specific aspects mentioned in a text, Aspect Category Detection (ACD), which classifies these aspects into broader categories, and Sentiment Classification, which determines the sentiment expressed towards each aspect (Do et al., 2019). Building upon these three subtasks, two main ABSA problems have emerged: Aspect Term Sentiment Analysis (ATSA) and Aspect Category Sentiment Analysis (ACSA). ATSA is concerned with classifying sentiments towards explicitly mentioned aspect terms, whereas ACSA focuses on the broader task of identifying and categorizing multiple aspect categories and their corresponding sentiments within a sentence (Zhou & Law, 2022). Due to the frequent occurrence of implicit aspect mentioned in text, this study investigates the ACSA problem.

ABSA has been widely employed across diverse domains including products (Geetha & Renuka, 2021), restaurants (Bensoltane & Zaki; 2022), hotels (Abdelgwad et al., 2022), medical domain (Han, Liu & Jing, 2020) and social media analysis (Alsayat, 2022; Patil & Kolhe, 2022).

Traditionally, ABSA systems primarily relied on rule-based and knowledge-based approaches which employed predefined linguistic patterns, relations, assumptions and heuristics to identify aspects and sentiments (Bayraktar et al., 2019; Ray & Chakrabarti, 2022; Rani & Jain, 2024; phan et al., 2023). Although knowledge-based methods provide the advantages of simplicity by eliminating the need for extensive training, they become increasingly time-consuming to develop as diversity and volume of data grows, struggling to capture nuances and variations in language or generalize to new domains (Runi & Jain, 2024). To address these challenges, machine learning-based and hybrid approaches emerged, integrating statistical models and additional knowledge sources. While ML-based ABSA systems automate the learning of features and patterns, supervised learning models, such as Naive Bayes (Webb et al., 2010), Support Vector Machines (SVM) (Noble, 2006) and Artificial Neural Networks (Agatonovic, 2000) primarily rely on training processes (Phan et al., 2023) and necessitate large amounts of human-annotated data (Bhatti et al., 2020; Huang et al., 2020). These models are highly dependent on domain-specific training data (Phan et al., 2023), constraining their ability to generalize across domains. This reliance poses challenges in extracting relevant aspects from textual data (L'Heureux et al., 2017).

Recent years have witnessed advancements in ABSA tasks driven by deep learning, enabling the extraction of crucial feature information and representation of this information in low-dimensional vectors (Li et al., 2020). Deep learning revolutionized ABSA by enabling models to automatically learn features without relying on manually crafted rules which are labor-intensive.

Convolutional Neural Network (CNNs) were among the first deep learning models which have been widely employed in ABSA due to their effectiveness in capturing n-gram features (Do et al., 2019). Poria et al. (2016) improved model performance by combining CNNs with linguistic patterns for aspect extraction. Gu et al. (2017) introduced a hierarchical CNN architecture designed to simultaneously implement aspect category detection and sentiment classification.

While CNNs excel at understanding local features, Recurrent Neural Networks (RNNs) can effectively model sequential dependencies within text. This enables RNNs to handle variable-length input sequences (Do et al., 2019). DL architectures like Long Short-Term Memory (LSTM) (Do, 2018) and Gated Recurrent Unit (GRU) (Setiawan et al., 2020) as variants of Recurrent Neural Network (RNN) have demonstrated exceptional performance in ABSA across various domains. However, traditional deep learning models, including both CNNs and RNNs, have limitations. CNNs struggle to understand sentence-level context and identify crucial entities for precise sentiment analysis. On the other hand, RNNs even in their advanced form like Bidirectional LSTMs, which can capture relationships and underlying meaning of input text (Rani & Jain, 2024), encounter challenges in fully capturing complex linguistic nuances (Phan et a., 2024). To address these limitations, researchers have explored hybrid models that combine RNNs with other techniques. For example, Chen et al. (2017) proposed bidirectional LSTM integrated with a Conditional Random Field (CRF) model for opinion target extraction to understand intricate linguistic patterns and enhance sentiment analysis performance.

While hybrid models, such as those combining RNNs and CRFs, have shown promise in addressing some of the challenges of traditional deep learning models, they continue to struggle with capturing complex semantic relationships and contextual information. To mitigate these limitations, attention mechanisms have been developed to focus on the crucial parts of the input and aspects as well as their contextual nuances (Zhou & Law, 2022). Early studies, such as ATE-LSTM applied an attention layer with bidirectional LSTM model to generate aspect-specific representations (Wang et al., 2016). Subsequent research proposed an attention encoder network (AEN) including multi-head attention (Song et al., 2019). Xu et al., 2020 introduced a multi-attention network (Man), which effectively extracted complex information between aspects and their context. These attention-based models have demonstrated strong performance in learning aspect-specific representations learning (Zhao et al., 2020). Gan et al. (2020) developed a sparse attention-based convolutional Neural Network (CNN) that excels at contextual semantic integration and extraction.

In addition to attention mechanisms, Furthermore, knowledge-based approaches have shown promise in identifying semantic relationships between words, aspects, and sentiments within text (Meškele & Frasincar, 2020). For instance, Tubishat et al. (2020) introduced a supervised aspect extraction algorithm which utilized pattern-based rules and achieved impressive results on customer review corpora.

Building on the achievements of attention mechanisms and knowledge-based methods, researchers have increasingly explored hybrid approaches that leverage the strengths of both methods. Meškele and Frasincar (2020) introduced the use of lexicalized domain ontology to reveal complex relationships between aspects and sentiment words within an integrated framework. A neutral attention model was proposed to determine sentiment polarity for the target aspect category (Zhou and Law, 2022). A two-step hybrid model was developed by Chauhan et al. (2020) for aspect term extraction (ATE), in which a dependency parser was employed to identify aspect-related phrases. These phrases were subsequently used as labeled data to train an attention-based bi-LSTM model. To incorporate diverse linguistic information, Li, et al. (2020) presented a bidirectional LSTM combined with self-attention. This model integrated part-of-speech (POS) tags, positional information and dependency parsing features which were combined with pre-trained word embeddings and processed through a bi-LSTM and self-attention layer.

Recent surveys conducted from 2022 to 2023 (Brauwers & Frasicar, 2023; Trisna & Jie, 2022; Dhanith & Prabha, 2023) reveal that a wide range of deep learning architectures are predominantly utilized for ABSA on modern data bases. These include Convolutional Neural Networks (CNNs) (Sadr et al., 2021; Wang et al., 2021), Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) (Do, 2018) or Gated Recurrent Unit (GRU) (Setiawan et al.,

2020) cells, Attention-based LSTMs (Zeng et al., 2019; Nguyen et al., 2018; Yang et al., 2019), and Transformers (Kumar et al., 2021; Hoang et al., 2019; Peng et al., 2022; Phan et al., 2022).

Despite their effectiveness, LSTM and CNN models encountered two primary limitations in ABSA. Firstly, their performance was frequently domain and dataset-specific, which adversely effected generalizability. Secondly, these models struggled to maintain consistently high accuracy levels. As a result, transformer-based models were proposed as promising alternative to overcome these challenges (Mughal et al., 2024). More recently, Graph Convolutional Networks (GCNs) have gained attention as a promising approach for ABSA (Phan et a., 2024). To leverage syntactic information inherent in language, graph neural networks (GNNs), a paradigm in neural network architecture (Scarselli et al., 2009), have proven to be an efficient tool to analyze dependency structures from parsed text (Zhou & Law, 2022). Sun et al. (2019) introduced convolutional over dependency tree (CDT) to capture the intricate dependencies between aspect words and other context words. In parallel work, Zhang et al. (2019) integrated a multi-layer graph convolutional network (GCN) with LSTM encoder to create aspect-specific features form dependency tree structures.

2.5 Semantic Similarity and Relatedness

Semantic similarity and relatedness have been widely used in the filed of sentiment analysis and has been applied to Aspect Category Detection (ACD) tasks (Rana & Cheah, 2016). Semantic similarity and relatedness are fundamental research areas in natural language processing (NLP) which are employed to understand textual content by quantifying the degree of semantic resemblance between terms (Mjumder et al., 2016). While often used interchangeably, these concepts differ notably. Semantic similarity is a subset of semantic relatedness, focusing specifically on taxonomic likeness between concepts. These models primarily depend on hierarchical relationships such as hypernymy (superordinate) and hyponymy (subordinate) and evaluate how closely terms fit within the same conceptual category (Lofi, 2015), whereas relatedness models cover a broader spectrum of semantic associations, expanding beyond taxonomic hierarchies to include synonyms, holonymy (part-whole relationships), and other non-taxonomic connections such as functionality and causality (AlMousa et al., 2021; Hussain et al., 2023; Zhu, Yang, Huang, Guo, & Zhang, 2019). Human judgement of these relationships extends beyond textual analysis; it involves a deeper conceptual understanding. As a result, computational models need access to comprehensive computer-readable knowledge resources (KRs), such as corpora or ontologies, to accurately assess similarity and relatedness (Hussain et al., 2023). Approaches for measuring these constructs can be divided into ontology-based and corpus-based approaches. Ontology-based approaches measure concept similarity based on the ontologies that define well-structured unambiguous representations of knowledge and structural knowledge bases (Lofi, 2015). These approaches represent knowledge as graphs, enabling the use of graph-theoretic principles to measure semantic relationships (Lastra-Díaz et al., 2021). In contrast, corpus-based models determine semantic similarity and relatedness through statistical analysis of word occurrences within large text corpora (Qu et al., 2018). Wordnet is a prominent instance of domain ontology. This expert-constructed lexical database organizes English words into sets of synonyms (synsets) interconnected by various semantic relations, such as hyponymy (is-a) and meronymy (part-of) (Zhou & Law, 2022). WordNet-based methods are used to effectively measure semantic similarity and relatedness by leveraging its precise and well-established semantic information. These methods are straightforward to implement and often achieve high levels of accuracy (Hussain et al., 2023). Freebase (Wang, Song, Li, Zhang, & Han, 2015) and YAGO (Zhu & Iglesias, 2017) are other significant ontologies that provide structured representations of knowledge within their respective domains. Ontology-based measures utilize the underlying graph structures to quantify semantic similarity. Edge counting estimates similarity by determining the shortest path length between concepts (nods) within a knowledge graph. Shorter path lengths indicate greater semantic similarity between concepts (Priyantina & Sarno, 2019; Wills & Mayer, 2020). Information content-based measures, such as Wu and Palmer (1994) similarly, combine both semantic distance (measured as number of edges between concepts) and depth of the least common subsumer (LCS) within the taxonomic hierarchy to provide a more comprehensive similarity computation (Lofi, 2015). The Wu and Palmer similarity between two concepts x_1 and $x_2$is calculated as follows:

$$Sim_{wup}(x_1, x_2) = 2 * \frac{depth(LCS(x_1, x_2))}{depth(x_1) + depth(x_2)}$$

To incorporate semantic richness, information content (IC) was introduced as a metric to compute the probability of a concept's occurrence within a corpus. This is calculated as IC(x) = -log p(x). Several similarity measures based on IC, such as Resnik, Lin, and Jian similarity, build upon this concept. While Resnik similarity directly evaluates the IC of the least common subsumer (LCS) for two concepts (as shown in Equation 2), Lin and Jian similarities further refine these calculations by introducing normalization factors (Araque et al., 2019; Lofi, 2015), enhancing the accuracy of similarity estimation.

$$Sim_{res}(x_1, x_2) = IC(LCS(x_1, x_2))$$

$$Sim_{lin}(x_1, x_2) = \frac{2 * IC(LCS(x_1, x_2))}{IC(x_1) + IC(x_2)}$$

$$Sim_{jc}(x_1, x_2) = \frac{1}{IC(x_1) + IC(x_2) - 2 * IC(LCS(x_1, x_2))}$$

Shifting focus from the structural realm of ontologies, Distributional semantics provides a corpus-based and data-driven approach for evaluating semantic similarity and relatedness which differ from ontology-based approaches that rely on structured knowledge bases. The core principle behind this approach is that words occurring in similar contexts are likely to be semantically related (Li, Zhou, & Li, 2015). Pointwise Mutual Information (PMI) is a well-established statistical measure of co-occurrence strength between words. It is computed using the log ratio of the joint probability of the two words occurring together to the product of their individual probabilities (Lofi, 2015|). A higher PMI value reflects a stronger relationship between words. The Pointwise Mutual (PMI) can be expressed as:

$$PMI(x_1, x_2) = \log \frac{p(x_1, x_2)}{p(x_1) * p(x_2)} = IC(x_1) + IC(x_2) - IC(x_1, x_2)$$

The practical applications of PMI extend to various domains, such as web search engines like Google and Baidu, where the frequency of search hits is used to estimate PMI values (Lofi, 2015). Cilibrasi and Vitanyi (2007) proposed Normalized Google Distance (NGD) as another metric for evaluating keyword relatedness based on search engine data. Wikipedia has served as a knowledge base for calculating PMI (Salahli, 2009).

Beyond co-occurrence statistics, distribution semantics often involves representing words as high-dimensional vectors, facilitating similarity evaluation through techniques such as cosine similarity. Cosine similarity is commonly employed to quantify the similarity between these word vectors, providing a numerical assessment of the semantic relatedness between the words they represent (Brown et al., 2023).

Semantic similarity and relatedness have been extensively applied to Aspect Category Detection (ACD) tasks (Rana & Cheah, 2016). Numerous techniques have been proposed to utilize these linguistic concepts for extraction of aspect category. Frequency-based approaches incorporated to semantic similarity measure such as Pointwise Mutual Information (PMI) to identify the semantic similarity between aspects and target entities (Li et al., 2015). Rule-based methods have also been investigated, employing techniques such as double propagation approach (DP) and sequential pattern mining. These approaches are often improved with semantic similarity measures, such as cosine similarity and Normalized Google Distance (NGD) to refine aspect extraction results (Liu et al., 2016; Kang & Zhou, 2017; Rana & Cheah, 2017).

In addition to rule-based approaches, topic modelling techniques that incorporated semantic similarity and relatedness have been employed to improve aspect extraction. By clustering words into semantically coherent topics, researcher have identified potential aspect terms with greater accuracy. Latent Dirichlet Allocation (LDA) is a well-established technique used in this context. Topic modelling enables researchers to classify aspect terms into predefined catgories based on their semantic similarity (Miller et al., 2016; Shms & Braani-Dastjerdi, 2017).

2.6 SMOTE

The performance of a classifier is not only dependent on the learning algorithm; the composition and distribution of data in each class also play a significant role in influence performance (Pradipta et al., 2021). One of the most critical challenges in machine leaning is dealing with imbalanced data (Krawczyk, 2016). When class distributions are imbalanced, classifiers often exhibit bias towards majority class, resulting in poor performance. This imbalance often leads to high error rates or even complete neglect of minority class(es) (Dablain et al., 2023). In imbalanced datasets, one class, known as minority or positive class is significantly underpresented compared to the other class, which is the majority or negative class. This imbalance can cause models to overlook or misclassify rare instances, leading to a higher error rate for the minority class (Pradipta et al., 2021). Addressing this challenge has been a major research focus over the past two decades (Fernández et al., 2018). One common approach to address imbalanced data is to use resampling techniques. These methods can be categorized into three groups: Undersampling methods which reduce the majority class and create subsets of the original dataset. Oversampling methods that increase the minority class by either replicating instances or creating new ones. Hybrid methods which combine undersampling and oversampling techniques (Pradipta et al., 2021). In 2002, Chawla et al. (2002) introduced the Synthetic Minority Oversampling Technique (SMOTE), a pioneering approach for oversampling imbalanced data. SMOTE aimed to address overfitting caused by simple replication-based oversampling. By creating new, synthetic instances, SMOTE helps the classifier improve its generalizability on unseen data. Unlike simple replication, this approach increases the number of minority class instances by creating new instances within a defined neighborhood of existing ones. This helps classifiers enhance their generalizability. The method focuses on "feature apace", considering the values and relationships of features rather than viewing data points individually (Fernández et al., 2018, p. 866).

Several studies have explored effectiveness of combining SMOTE with various techniques. Zeberga and Gebremariam (2022) addresses the issue of imbalanced data in multi-label aspect categorization. The paper proposes a method combining oversampling techniques and ensemble learning to improve classification performance on imbalanced datasets. The paper explores the use of Synthetic Minority Over-sampling technique (SMOTE) to balance the dataset by generating synthetic samples for minority classes. The results show that the combination of techniques such as SMOTE and ensemble learning significantly improves the classification metrics. In a similar study conducted by Nourbakhsh et al. (2022), the authors proposed using SMOTE to generate synthetic samples for minority classes, which helps balance the dataset. The results indicate that the combination of SMOTE and ensemble learning significantly improves classification metrics, particularly recall and F-1score, for minority classes. Tesfa et al. (2024) aim to evaluate the sentiment polarity and categorize comments into specific aspects of comments collected from Facebook. The results of the study show that The SVM model trained with TF-IDF and SMOTE oversampling achieved the highest accuracy of 98% for aspect-based sentiment classification. Similarly, the study conducted by Saputra & Setianwan (2023) focuses on developing an ABSA system to classify sentiments and aspects of movie reviews extracted from Twitter. The research demonstrated that the combination of TF-IDF, FastText, and SMOTE significantly improves the performance of RNN model.

2.7 Evaluation Metrics

Evaluating model performance is an important step in the machine learning process to assess the effectiveness and reliability of the model. It involves multiple metrics which are selected depending on the task. Commonly used metrics include accuracy, precision, recall and F-1 score. Accuracy measures the ratio of correct predictions to total number of predictions. While being useful, accuracy can be misleading when the data is imbalanced (Nguyen, 2024).

Precision and recall, along with their combinations capture information about the "rates and kind of errors made" by the model (Powers, 2011, p. 38). Precision is the ratio of true positives divided by the total predicted positives. It is crucial when false positives (false alarms) are costly.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall is calculated as the ratio of true positive instances to total actual positives. it is useful in scenarios where the cost of false negatives is high.

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

The shortcoming of precision and recall is that neither of them assesses how well the model handles negative cases. In such cases, models such as inverse recall and inverse precision can be utilized to capture information about true negatives (Powers, 2011).

The F1 score is the harmonic mean of precision and recall, providing a balanced evaluation of model's performance. These metrics are essential for tasks where the false positives and false negative carry different costs in fields such medical diagnosis or fraud detection (Garcia, 2024).

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Other emerging metrics, such as the area under the Receiver Operating Characteristic (ROC) curve (AUC-ROC) and precision-recall curves, provide deeper insights into model's performance, particularly in the presence of imbalanced datasets (Hernandez, 2024). AUC-ROC is utilized in different fields such as medical diagnostics or screening tests to show the trade-offs between true positive and false positive rates (Powers, 2020).

3. Methods

In this chapter, we present the description of dataset, methods developed to analyze text data and evaluate results in this study.

3.1 Data Description and Collection

A dataset of 152,502 tweets about McDonald's was collected from Twitter using a Google Chrome Extension developed by Web and Internet science Research Group of University of Southampton (University of Southampton, n.d.). They were scraped from October 10, 2023 to June 3, 2024. The tweets were filtered using specific keywords. The data was saved in spreadsheet form including different components such as title, contents, data, author, etc. Then the information was saved as HTML files.

3.1.1 Labeled Data

Annotated datasets play a highly important role in machine learning. In this study, 1000 tweets were manually labeled and categorized by two annotators focusing on assigning categories, identifying relevant aspects, and determining sentiment. The annotation process involved three steps: region specification, where tweets were divided into distinct regions based on topics or themes; category and aspect assignment, classifying these regions based on a predefined criteria illustrated in table 1; and sentiment analysis, labeling the sentiment as positive, neutral, or negative withing each region. The final annotated dataset includes 1,750 instances. This increase results from the detailed annotation of multiple regions within some tweets, which leads to a more nuanced and accurate analysis of content.

No.	Category	Aspect
1	Core Restaurant Experience	Food
		Customer Service
		Products
2	Brand Perception and Loyalty	Brand Perception
		Loyalty
		Brand Competition
3	Corporate and Social Responsibility	Ethical Responsibility
		Public Health Impact
4	Value for Money	Price
5	Promotions and Marketing	Marketing Strategy
		Sponsorships and Events
		Promotions
6	Other	General

Table 1: Categories and Aspects

3.1.1.1 Rational for Category Selection

The categories identified for data labeling were selected due to their relevance to the core aspects of customer experience, brand management and business within the restaurant industry.

Core Restaurant Experience: This category encompasses the core dimensions of a restaurant's operation that directly influence customer satisfaction and loyalty. According to Albayrak (2015) and Muscat et al. (2019), customer's perception of restaurant quality can be affected by key factors such as product and service quality. These components along with product range and restaurant atmosphere are integral to restaurant experience which in turn influence repeat visits. Food quality in particular impacts perceived value, customer satisfaction, and loyalty (Wirtz et al., 2000; Lin, 2010; Bengül & Güven, 2019).

Brand Perception and loyalty: Brand Perception and customer loyalty are fundamental to long-term success of businesses. Loyal customers are valuable assets that generate a stable revenue stream through repeat purchases (Evanschitzky et al., 2012; McMullan & Gilmore, 2008). A positive brand image boosts customer satisfaction improves perceived value and fosters loyalty (Ryi et al., 2008). This category investigates customer perceptions of brand which is a critical factor that significantly influence purchasing decisions.

Corporate and Social Responsibility: Corporate Social Responsibility (CSR) is a strategic necessity for businesses. By prioritizing societal well-being (Han et al., 2020; Lo, 2020), businesses try to strengthen customer loyalty and bolster their reputation (Han, Yu, & Kim, 2019; Lee et al., 2013). This category reflects consumer perceptions of a company's CSR efforts and their influence on brand loyalty and overall image.

Value for Money: Price and perceived value are crucial determinants in customer choice, particularly in the restaurant industry. This is closely tied to customer satisfaction and loyalty, as consumers are more likely to return if they believe they receive good value (Albayrak, 2015 & Kwon, 2020).

Promotions and Marketing: Effective marketing and promotional activities play an important role in customer acquisition and retention. Promotions involve initiatives aimed at simulating customer purchasing (Sukirno et al., 2014) which significantly impact purchase intentions. Moreover, effective marketing delivers consistent value to build customer loyalty (wood, 2008)

Other: This category encompasses tweets that do not fit neatly within the specifed categories.

3.1.1.2 Example labeled Tweets

Tables 2 to 10 presents illustrative examples of labeled tweets, showcasing the assigned categories, corresponding aspects and associated sentiment classifications. In example 2, " Why did McDonald’s give me a mcchicken instead of an apple pie it’s a tragedy beyond belief" the sentiment polarity of aspect 'Customer Service' within category 'Core Customer Experience’ is negative. In example 8, " So messed up my order for the four billionth time. McDonald, your burgers are overpriced i want my money back.", the sentiment polarity of aspect 'Customer Service' within category 'Core Restaurant Experience' (So messed up my order for the four billionth time.) is negative, and aspect 'Price' within category 'Value for Money' (McDonald, your burgers are overpriced i want my money back.) is also negative.

Example 1			
why can't McDonald's serve breakfast all day? all I want is a sausage mcgriddle			
Region	**Category**	**Aspect**	**Classification**
why can't McDonald's serve **breakfast** all day?	Core Restaurant Experience	Products	Negative
all I want is a **sausage mcgriddle**	Core Restaurant Experience	Products	Positive

Table 2: Labeled Tweet Example 1

Example 2		
Why did McDonald’s give me a mcchicken instead of an apple pie it’s a tragedy beyond belief		
Category	**Aspect**	**Classification**
Core Restaurant Experience	Customer Service	Negative

Table 3: Labeled Tweet Example 2

Example3			
I simply dislike all fast food breakfast McDonald's hash brown get a pass			
Region	**Category**	**Aspect**	**Classification**
I simply dislike all fast food breakfast	Core Restaurant Experience	Food	Negative
McDonald's hash brown get a pass	Core Restaurant Experience	Products	Positive

Table 4: Labeled Tweet Example 3

Example 4			
coworker said he thought about getting a mcgriddle but remembered how mad i her when he gets mcdonald's so he didnt			
Region	**Category**	**Aspect**	**Classification**
coworker said he thought about getting a mcgriddle	Core Restaurant Experience	Products	Neutral
but remembered how mad i her when he gets mcdonald's so he didnt	Brand Perception and Loyalty	Brand Perception	Negative

Table 5: Labeled Tweet Example 4

Example 5		
The guy at McDonald's is set on getting my name correct. Love that. Small gestures make a big difference.		
Category	**Aspect**	**Classification**
Core Restaurant Experience	Customer Service	Positive

Table 6: Labeled Tweet Example 5

Example 6			
McDonalds is a weird restaurant. I had to order my food on a giant table, the portion of frys was humongous, the straw for my drink was super wide, and my chicken sandwich came in a bag.			
Region	**Category**	**Aspect**	**Classification**
McDonalds is a weird restaurant.	Brand Perception and Loyalty	Brand Perception	Negative
I had to order my food on a giant table	Core Restaurant Experience	Ambience	Neutral
the portion of frys was humongous	Core Restaurant Experience	Products	Neutral
the straw for my drink was super wide, and my chicken sandwich came in a bag.	Core Restaurant Experience	Customer Service	Negative

Table 7: Labeled Tweet Example 6

Example 7			
How do you block McDonalds on just eat. I don't have a compulsion to buy it or anything I'm just boycotting.			
Region	**Category**	**Aspect**	**Classification**
How do you block McDonalds on just eat.	Brand Perception and Loyalty	Brand Perception	Negative
I don't have a compulsion to buy it or anything I'm just boycotting.	Corporate and Social Responsibility	Ethical Responsibility	Negative

Table 8: Labeled Tweet Example 7

Example 8			
So messed up my order for the four billionth time. McDonald, your burgers are overpriced i want my money back.			
Region	**Category**	**Aspect**	**Classification**
So messed up my order for the four billionth time.	Core Restaurant Experience	Customer Service	Negative
McDonald, your burgers are overpriced i want my money back.	Value for Money	Price	Negative

Table 9: Labeled Tweet Example 8

Example 9		
Interesting article from on child labour in the food industry. In nutshell: Big brands, like McDonald's are taking steps to eliminate child labour from their supply chain.		
Category	**Aspect**	**Classification**
Core Restaurant Experience	Corporate and Social Responsibility	Positive

Table 10: Labeled Tweet Example 9

3.1.1.3 Distribution of Tweets by Sentiment, Category, and Aspect

Table 11 represent distribution of tweets associated with each sentiment. Table 12 represent distribution of tweets associated with each category. Table 13 illustrates the distribution of tweets related with each aspect.

Sentiment	Count	Percentage
Neutral	397	36.93
Negative	436	40.55
Positive	242	22.51

Table 11: Distribution of Tweets by Sentiment

Category	Count	Percentage
Core Restaurant Experience	433	41.2
Brand Perception and Loyalty	204	18.97
Corporate and Social Responsibility	132	12.27
Promotions and Marketing	46	42.79
Value for Money	45	41.86
Other	205	19.06

Table 12: Distribution of Tweets by Category

Aspect	Count	Percentage
Food	115	10.69
Customer Service	124	11.53
Products	203	18.88
Brand Perception	104	9.67
Loyalty	55	5.11
Brand Competition	44	4.09
Ethical Responsibility	120	11.16
Public Health Impact	13	1.2
Price	46	4.27
Marketing Strategy	20	1.86
Sponsorships and Events	7	0.65
Promotions	19	1.76
General	205	19.06

Table 13: Distribution of Tweets by Aspect

3.1.1.4 Inter-Annotator Agreement

Inter-annotator agreement (IAA), also referred to as inter-rater reliability is a measure utilized to assess the degree of consensus and consistency between annotations assigned by multiple human annotators who label the same data (Landis & Koch, 1977). It plays an important role in research areas such as sentiment analysis which is based on subjective data (Krippendorff, 2018). Various statistical metrics are used to measure inter-rater reliability with Cohen's Kappa (Cohen, 1960) being a commonly used instance.

3.1.1.4.1 Cohen's Kappa

Cohen's Kappa metric is often employed to evaluate the degree of agreement between two annotators in a classification problem. It ranges from -1 to +1 and considers the observed agreement between raters (P_o) and the probability of the random agreement (expected agreement, Pe) (Galvez-Hernandez & Kratz, 2024). Landis and Koch (1977) suggested to interpret Cohen's Kappa as poor (<0.00), slight (0.00-0.2), fair (0.21-0.4), moderate (0.41-0.6), substantial (0.61-0.8) and almost perfect (0.81-1). The formula for Cohen's Kappa is:

$$\kappa = \frac{p_0 - p_e}{1 - p_e}$$

Kappa scores of **0.8939** for sentiment, **0.8392** for category and **0.7604** for aspect in this study indicates a high level of agreement between the annotators. It suggests that the annotations are highly reliable.

3.1.1.4.2 Observed Agreement

The observed agreement refers to the proportion of instances where the annotators agreed on the same label or category. In this study, the observed agreement is **0.9367** for sentiment, **0.8920** for category, and **0.8065** for aspect classification which indicates a high level of agreement between the two annotators and that they agreed on **93.67%** of instances for sentiment, **89.20%** for category and **80.65%** for aspect classification.

3.1.1.4.3 Expected Agreement

The expected agreement is the proportion of instances where the annotators would agree by chance. The expected agreement in this case is **0.4035** for sentiment, **0.3288** for category, **0.1923** for aspect which is relatively low. It suggests that annotators have not randomly labeled the text data.

3.1.1.4.4 Confusion Matrix

A confusion matrix is a visualization tool which is often employed to provide a detailed breakdown of classification problems (Sokolova et al., 2006). It compares the number of ground truth instances to the predicted class labels (Powers, 2020).

Neutral	Positive	Negative	Sentiment
16	18	424	Negative
11	212	7	Positive
371	11	5	Neutral

Table 14: Cohen's Kappa Confusion Matrix - Sentiment

Value for Money	Promotions and Marketing	Other	Corporate and Social	Core Restaurant Experience	Brand Preception	Category
2	3	8	3	3	187	Brand Preception
1	1	11	4	424	6	Core Restaurant Experience
0	0	9	114	5	2	Corporate and Social
3	7	170	6	8	5	Other
4	29	5	3	2	1	Promotions and Marketing
35	5	4	2	1	2	Value for Money

Table 15: Cohen's Kappa Confusion Matrix - Category

Sponsorships and Events	Public Health Impact	Promotions	Products	Price	Marketing Strategy	Loyality	General	Food	Ethical Responsibility	Customer Service	Brand Preception	Brand Competition	Aspect
0	0	3	2	2	2	1	2	0	1	1	1	25	**Brand Competition**
0	0	1	3	0	0	6	1	0	1	0	80	1	**Brand Preception**
1	0	0	2	0	1	0	3	3	2	108	2	1	**Customer Service**
0	3	0	0	0	0	1	2	0	107	3	0	0	**Ethical Responsibility**
0	0	1	11	3	0	0	4	92	0	0	0	0	**Food**
2	2	2	4	3	2	2	188	4	3	5	6	3	**General**
0	0	0	0	1	1	38	2	0	1	4	10	3	**Loyality**
1	0	4	2	1	8	2	0	0	0	0	1	3	**Marketing Strategy**
0	0	2	2	31	1	1	1	4	0	0	0	2	**Price**
0	0	0	174	0	0	1	1	9	0	1	1	0	**Products**
0	0	5	0	2	5	2	2	2	0	0	2	4	**Promotions**
0	8	0	1	0	0	0	1	1	5	2	0	0	**Public Health Impact**
3	0	0	2	3	0	1	0	0	0	0	0	2	**Sponsorships and Events**

Table 16: Cohen's Kapa Confusion Matrix - Aspect

Inter-annotator agreement calculated using Cohen's Kappa metric identified some discrepancies in the labeling of some tweets. To ensure data quality, disagreements were resolved through collaborative re-evaluation and consensus discussions, leading to a final, consistent labeled dataset.

3.2 Model Selection

In this study, we propose an Enhanced BERT-based multi-task classification model that leverages the strengths of pre-trained BERT embeddings with bidirectional LSTM (BiLSTM) and Transformer encoder layers. The model incorporates BiLSTM layers to capture sequential dependencies and Transformer encoder layers to model intricate inter-token relationships.

3.2.1 Data Preprocessing and SMOTE Application

The initial dataset was loaded from a CSV file, with sentiment, category, and aspect labels mapped to integers using predefined mappings.

3.2.1.1 Tokenization and Normalization

To prepare the text data for tokenization, a clean_text function is applied to ensure that all text inputs are valid strings, preventing potential processing errors. The cleaned text is then tokenized using the 'BertTokenizerFast' from the Hugging Face Transformers library. This tokenizer lowercases text, performs WordPiece tokenization to handle rare or out-of-vocabulary words and special characters, and applied padding/truncation for consistent input length.

3.2.1.2 Handling Class Imbalance with SMOTE

To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. SMOTE generates synthetic samples for minority classes, ensuring a balanced dataset and preventing model bias towards the majority class. Before applying SMOTE, a custom function was implemented to compare the number of instances for each label before and after SMOTE. The results are illustrated in tables 17, 18, 19.

The processed data is then divided into training (80%) and test (20%) sets. SMOTE is then applied to the training set to ensure balanced class distribution.

Aspect Label	Added by SMOTE	Percentage Increase
General	254	162.82%
Brand Perception	118	143.90%
Food	128	136.17%
Brand Competition	50	128.21%
Ethical Responsibility	166	180.43%
Price	75	182.93%
Customer Service	118	118.00%
Products	192	119.25%
Loyalty	57	118.75%
Public Health Impact	25	277.78%
Marketing Strategy	32	177.78%
Sponsorships and Events	15	250.00%
Promotions	36	257.14%

Table 17: Instances added by SMOTE - Aspect

Category Label	Added by SMOTE	Percentage Increase
Core Restaurant Experience	443	125.14%
Other	254	162.82%
Brand Perception and Loyalty	227	134.32%
Corporate and Social Responsibility	189	187.13%
Promotions and Marketing	81	207.69%
Value for Money	72	175.61%

Table 18: Instances added by SMOTE - Category

Sentiment Label	Added by SMOTE	Percentage Increase
Negative	568	160.91%
Neutral	453	144.73%
Positive	245	126.29%

Table 19: Instances added by SMOTE - Sentiment

3.2.2 BiLSTM for Sequential Contextualization

Our model leverages BiLSTM layer to enrich BERT embeddings with additional sequential context. By processing text sequences in both forward and backward directions, BiLSTM captures contextual information from surrounding words, improving each token representation. This bidirectional approach enhances the model's ability to capture the sequence, providing a more comprehensive contextual understanding compared to unidirectional LSTM. BiLSTM networks are variant of LSTM that processes input data in forward and backward directions. The bidirectional nature of BiLSTM network allows it to analyze input data from both and future time frames, unlike a standard LSTM, which are limited to processing information in a single direction from the past. As a result, BiLSTM can potentially overcome delays in capturing future context.

3.2.3 Transformer Encoder for Enhanced Contextual Representation

Subsequently, the BiLSTM outputs are fed into a Transformer encoder layer for further processing. Transformer encoder is designed to further refine the contextual representations by employing multi-head attention, enabling the model to focus on different segments of sequence.

This process is essential for capturing intricate dependencies within the text, enabling the model to relevant information for accurate classification.

3.2.4 Classification Layers and Output Processing

The final representation capturing the entire input sequence is taken from the hidden state of the [CLS] token in the final layer of the Transformer. This representation is subsequently fed into three distinct classification layers to predict aspect, category, and sentiment. Each transformer layer performs a linear transformation, followed by a sofmax function, to generate the probability distribution over the respective classes.

3.2.5 Training Procedures and Evaluation

The model is trained for six epochs utilizing the AdamW optimizer with learning rate of 1e-5. A linear learning rate scheduler with warm-up is used to optimize learning rate adjustment. Each training batch, consisting of 16 samples, calculates the sum of cross-entropy losses for three tasks (aspect, category, and sentiment classification). The model's performance is monitored through calculation of average loss per epoch.

To evaluate the impact of SMOTE, two model variants were trained: one using SMOTE-applied data and one with original dataset. Both models shared the same architecture and hyperparameters, ensuring direct comparison of their performance on the test set. Also, the model was trained for each of the following architectures: BERT only, BERT + LSTM, and BERT + LSTM + Transformer. Based on evaluation metrics, the BERT + LSTM + Transformer with SMOTE was selected for further analysis and application.

After training model performance is evaluated using metrics such as precision, recall, F1-score and accuracy for each classification task. Visualization such as F1-comparisons are generated to interpret model's performance.

3.3 Application of the Model to New Dataset

In addition to the initial model development and evaluation, the Enhanced Bert-based model is applied to a new dataset of real-world tweets about McDonald's. This dataset is selected and complied to ensure it contains a wide range of tweets that specifically mention or discuss McDonald's. This dataset provides valuable opportunity to investigate customer satisfaction and critical feedback. The main object of this phase is to leverage the model's capabilities to predict and categorize sentiments across different aspects and categories. The predicted sentiments are then systematically saved to visualize trends and pinpoint recurring issues and areas of concern.

4. Results

This chapter presents an overview and evaluation of the proposed Enhanced BERT-based multi-task classification model for sentiment, aspect, and category identification. The chapter is organized as follows: Section 4.1 compares the performance of different model architectures (BERT, BERT+LSTM, and BERT+BiLSTM+Transformer), including the impact of applying SMOTE, through detailed metrics and visualizations. Section 4.2 demonstrates the model's effectiveness on large-scale dataset of 151,502 tweets and provides in depth analysis of negative sentiment, supported by visualizations and key insights.

4.1 Results of Comparative Analysis of Model Architecture

Figure 3 presents a bar chart comparing F1-scores for sentiment, aspect, and category classification across three different model architectures: BERT only, BERT+LSTM, and BERT+LSTM+Transformer trained on dataset with SMOTE applied. Based on the results, all three models perform relatively well across the tasks. However, BERT+LSTM+Transformer model achieved the highest F1scores in all three tasks (Aspect:0.7756, Category: 0.8457, Sentiment: 0.8563), demonstrating a slight edge in capturing nuanced sentiment patterns and better performance in multi-task classification.

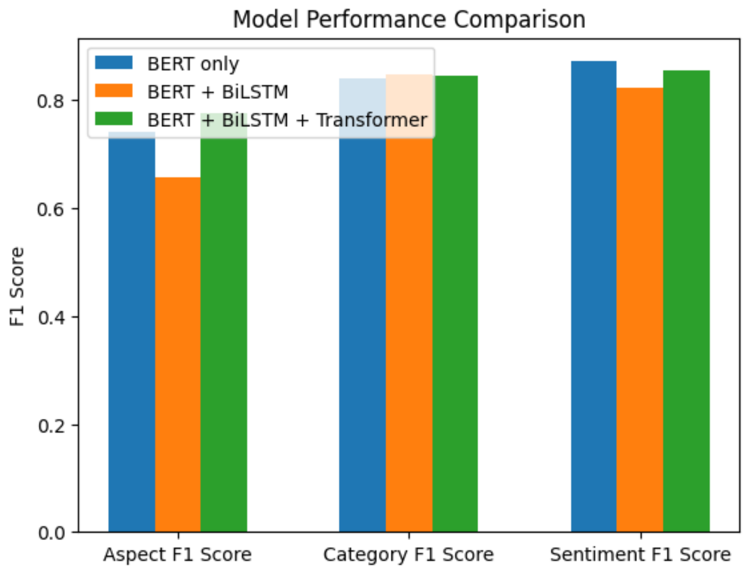

Figure 3: Model Performance Comparison with SMOTE

Figures 4, 5, and 6 present a comparative analysis of F1 scores for aspect, category, and sentiment classification, respectively, between models trained with and without SMOTE. The results clearly demonstrate that the application of SMOTE significantly enhances model performance across nearly all labels.

Figure 4 illustrates the impact of SMOTE on aspect classification task. The model trained with SMOTE consistently outperforms the model without SMOTE for most aspect labels. For instance, the F1-scores for 'General' and 'Products' increased from 0.5294 (No SMOTE) to 0.8750 (SMOTE), and 0.6129 to 0.8268, respectively. Labels such as 'Loyalty', 'Public Health Impact', 'Marketing Strategy', 'Sponsorship and Events' and 'Promotions' also exhibit marked improvements, emphasizing SMOTE's effectiveness in enhancing the model's ability to handle imbalanced data.

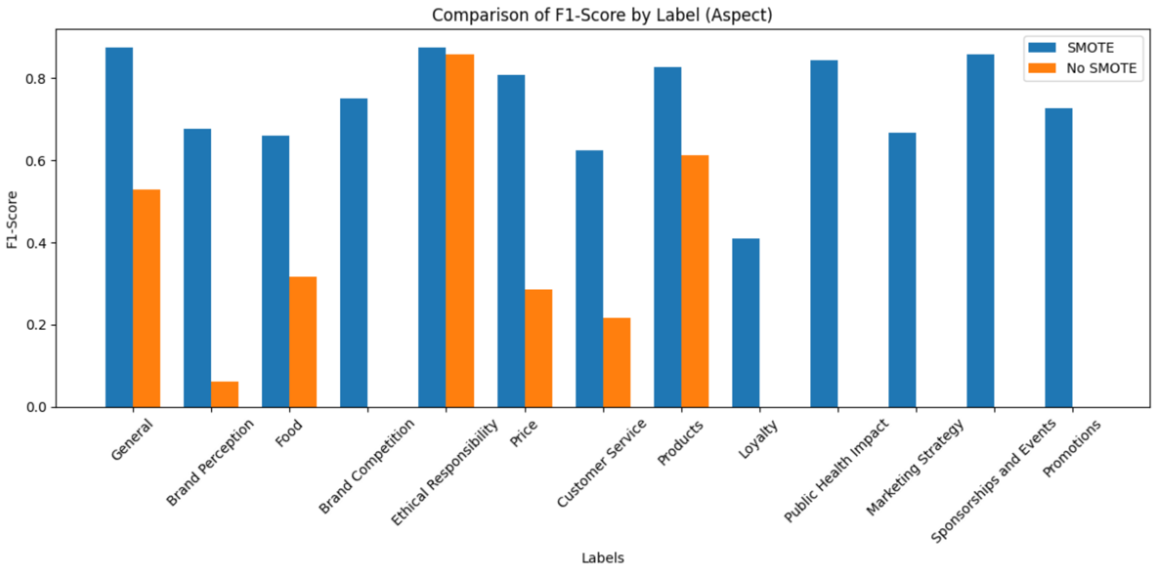

Figure 4: Impact of SMOTE on aspect classification task

Figure 5 highlights the positive impact of SMOTE on category classification. The 'Core Restaurant Experience' category, for instance, saw an F1-score increase from 0.7129 to 0.8603. Similarly, the 'Other' category benefited substantially, with its F1-score increasing from 0.4286 to 0.9045. labels such as 'Brand Perception and Loyalty', 'Promotions and Marketing' and 'Value for Money' also exhibit marked improvements, underscoring SMOTE's effectiveness in addressing class imbalance challenge and enhancement of model performance.

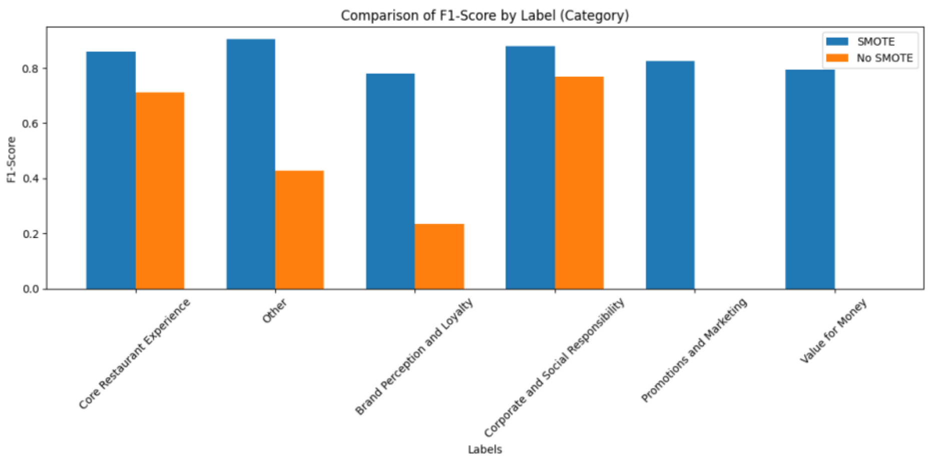

Figure 5: Impact of SMOTE on category classification task

Figure 6 demonstrates the impact of SMOTE on sentiment classification. The F1-score for 'Negative' sentiment classification increased from 0.6364 to 0.9020 with SMOTE. Similarly, 'Positive' and 'Neutral' sentiments also saw improvements, highlighting SMOTE's effectiveness in providing a more balanced and accurate sentiment classification model.

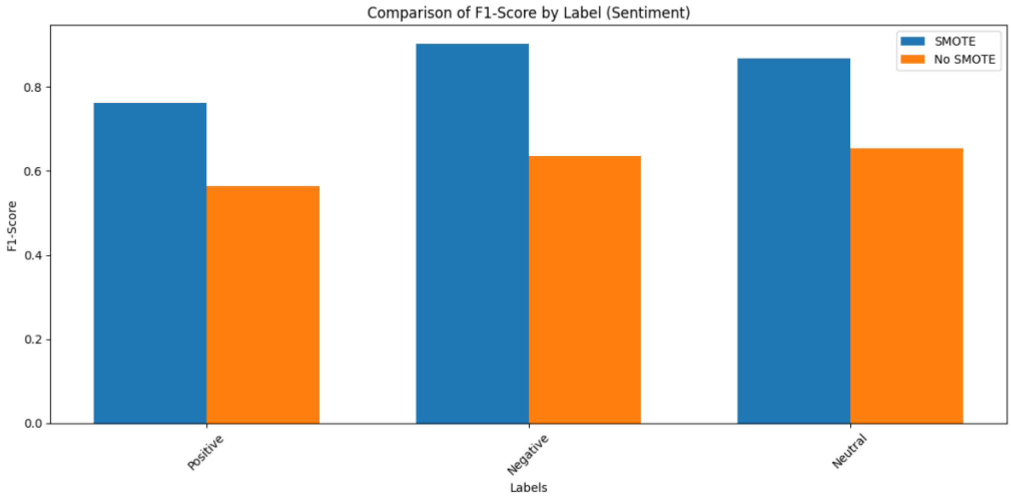

Figure 6: Impact of SMOTE on sentiment classification task

4.2 Results of Model Deployment on Large-scale Twitter Dataset

Based on the analysis of 151,502 tweets related to McDonald's, figures 7 to 10 provide insights into public sentiment across various aspect and categories. The results highlight both the most positively and negatively perceived areas for brand.

In terms of positive statement, the bar charts indicate that 'Products' and 'food' (aspects associated with 'Core Restaurant Experience' category) are among the most positively perceived aspects. Additionally, 'Loyalty' (an aspect associated with 'Brand Perception and Loyalty' category) also garners significant positive sentiment. These findings indicate that customers generally value their overall dining experience and quality of the products offered by McDonald's. The positive perception of 'Core Restaurant Experience' is primarily driven by satisfaction with 'Food' and 'Products'.

On the negative side, the bar charts highlight 'Ethical Responsibility' and 'Public Health Impact' (aspects associated with 'Corporate and Social Responsibility' category) and 'Customer Service' (an aspect associated with 'Core Restaurant Experience' category), as well as 'Brand Perception' and 'Brand Competition' (aspects associated with 'Brand Perception and Loyalty' category) as primary sources of negative sentiment. While the 'Core Restaurant Experience' is generally positive, Figure 8 shows a significant portion of negative sentiment within category, which is primary driven by negative sentiment towards 'Customer Service'. The negative sentiment in

'Corporate and Social Responsibility' which is driven by dissatisfaction with 'Ethical Responsibility' and 'Public Health Impact' reflects concerns about McDonald's ethical practices and social responsibilities.

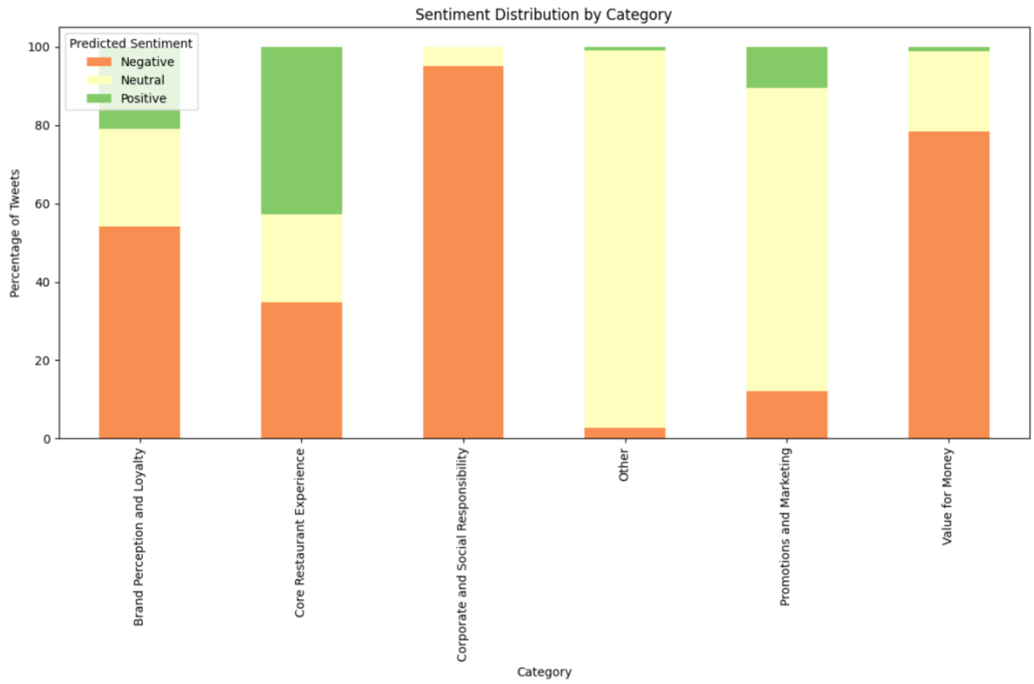

Figure 7: Sentiment Distribution by category for Tweets Database

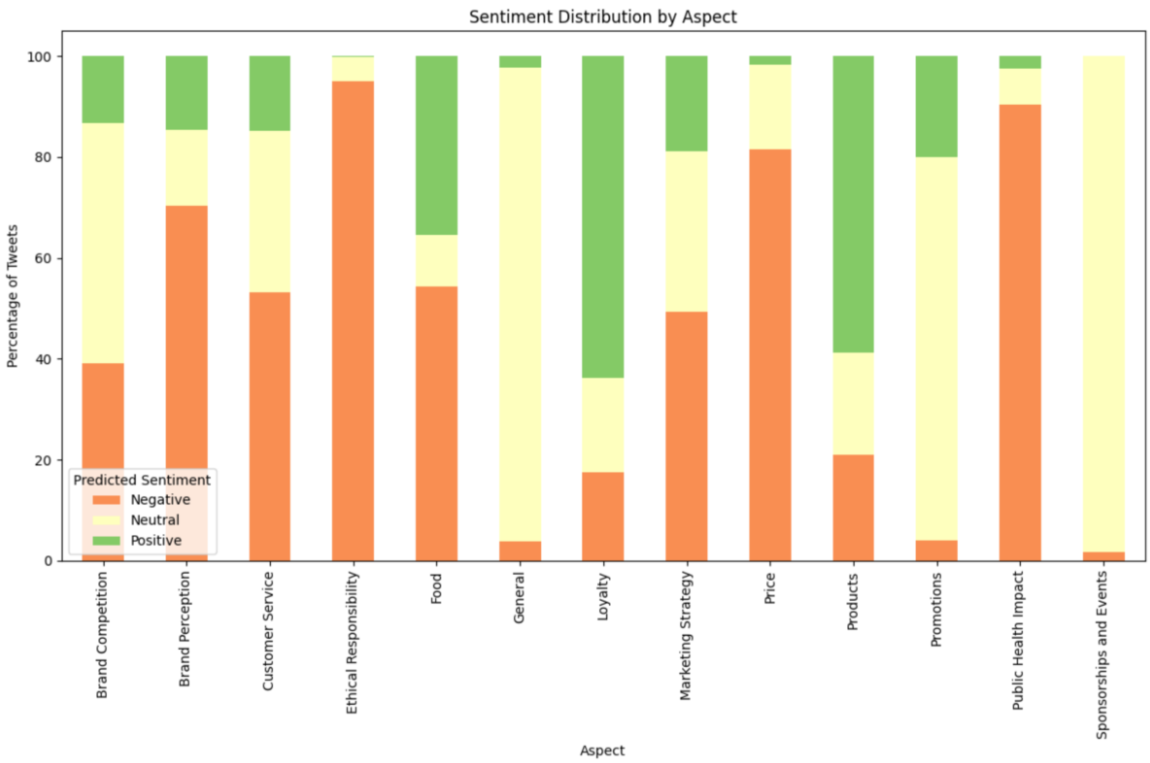

Figure 8: Sentiment Distribution by Aspect for Tweets Dataset

Figure 9 illustrates the distribution of negative sentiment across different categories. 'Core Restaurant Experience' and 'Corporate and Social Responsibility' emerge as primary drivers of negative sentiment, with 36.8% and 30.4% of negative tweets respectively. This indicates widespread dissatisfaction with in-store experiences and McDoanld's approach to social and ethical responsibility. Additionally, 'Brand Perception and Loyalty' contributes to negative sentiment (23.6%) highlighting concerns about the brand's image and customer retention which as illustrated in Figure 4.6 is driven by negatively perceived 'Brand Competition' and 'Brand Perception' aspects.

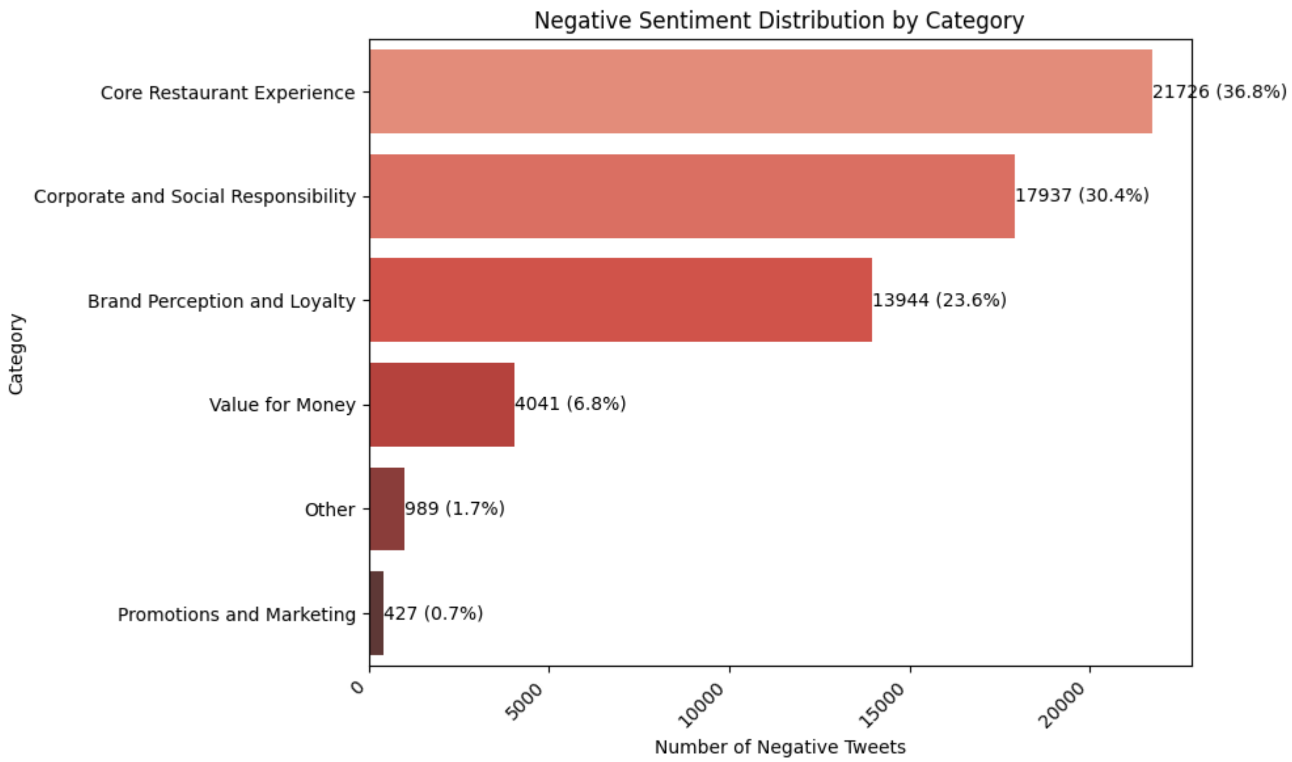

Figure 9: Negative Sentiment Distribution by Category for Tweets Corpus

Figure 10 further focus on these findings by investigating negative sentiment distribution across aspects. It shows that 'Ethical Responsibility', 'Brand Perception', 'Customer Service' and 'Price' are among most frequently occurring topics in negative tweets.

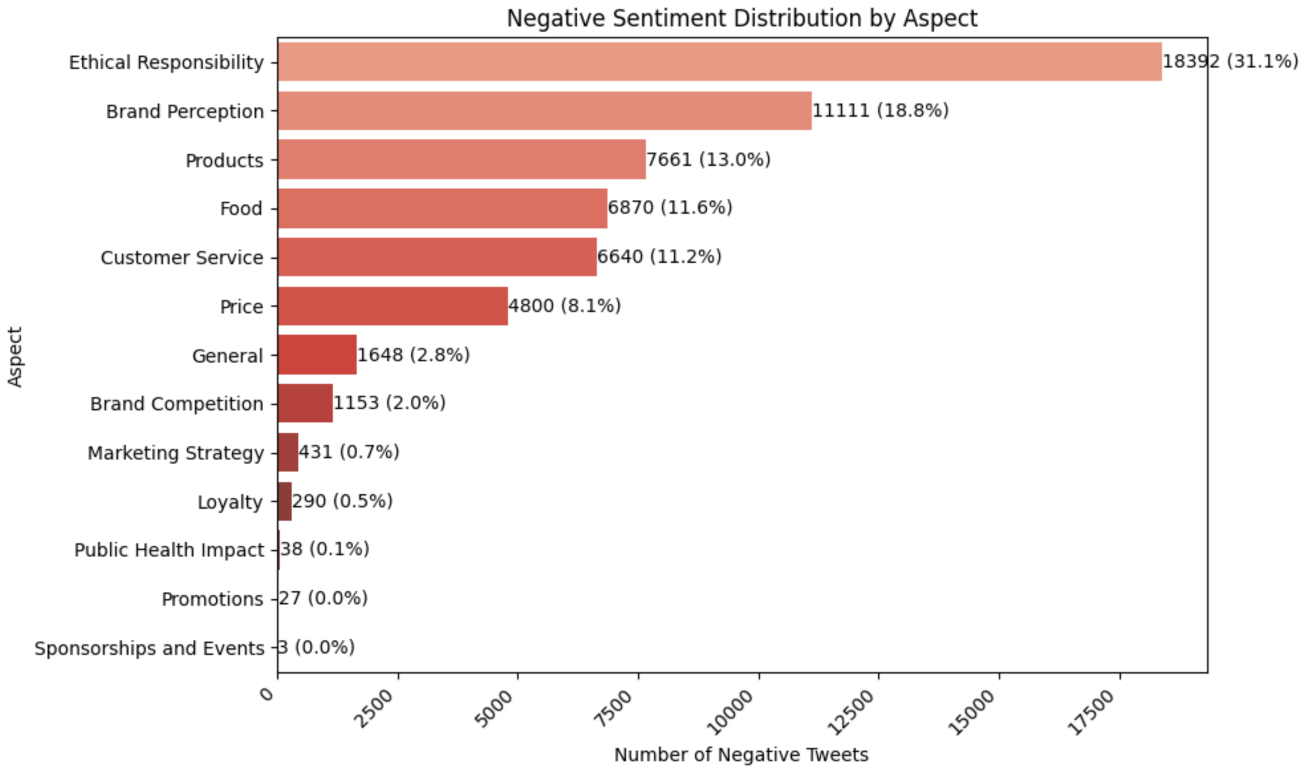

Figure 10: Negative Sentiment Distribution by Aspect for Tweets Dataset

5. Discussions

While the literature on ABSA is rich with theoretical models and numerous studies have focused on developing theoretical models for ABSA, this study distinguishes itself by bridging the gap between theory and practice. It applies an innovative ABSA model to real-world dataset of McDonald's tweets. By analyzing these tweets through the lens of our proposed model, we have demonstrated its effectiveness in investigating consumer sentiment and provided actionable insights for the brand. Additionally, analyzing McDonald's tweets offers a unique opportunity for large-scale sentiment analysis. As a global fast-food giant that consistently adapts to industry trends, McDonald's offers a rich dataset for exploring complexities of consumer and brand perception.

The current study was two-fold: First, we developed an Enhanced BERT-based model for ABSA, integrating advanced components to improve performance. Second, we applied the model to analyze real-world tweets related to McDonald's to understand customer opinions.

5.1 Model Architecture and Performance Evaluation

The Enhanced BERT model developed in this study expanded on the standard BERT's capabilities by incorporating a BiLSTM layer and a Transformer Encoder layer, tailored for multi-task classification of tweets. While BERT provides robust contextual embeddings, the BiLSTM adds deeper sequential understanding by capturing dependencies between words in both directions within text. The Transformer Encoder further improved this by using self-attention to prioritize the most relevant elements of the sequence. This multi-task architecture, with distinct heads for aspect, category, and sentiment classification, enabled the model to generalize better and learn more effectively from different tasks, contributing to enhanced overall performance.

Additionally, combining the model with SMOTE enhances its performance, particularly for underrepresented classes, by addressing class imbalance. The model's integration of advanced components, including contextual understanding, sequential modeling, and task-specific learning equipped the model to handle the complexities of tweets, making it particularly well-suited for applications that require a deep understanding of multiple inter-related elements.

Findings from this research show that the Enhanced BERT model consistently achieved high performance in the aspect, category, and sentiment classification tasks as evidenced by high F1-scores. Specifically, the model achieved F1-score of 0.85 for sentiment, 0.84 for category and 0.77 for aspect classification. As illustrated in Figures 3, 4, 5, 6 in the methods section, these results confirm the model's effectiveness, especially in handling imbalanced data through the use of SMOTE.

5.2 Strategic Implications from Sentiment Analysis of McDonald's-Related tweets

The analysis of 151,502 tweets about McDonald's offers vauable insights into public sentiment across various categories and aspects, which can inform strategic decision-making. The findings highlight the complex landscape of customer sentiment toward McDonald's, which the company must address to strengthen its brand image and customer loyalty. The positive sentiment towards 'Products' and 'Food' within the 'Core Restaurant Experience' category demonstrates McDonald's success in delivering high-quality products that satisfy customer expectations. Consumers are paying more attention to the food quality of fast-food restaurants (Rajput & Gahfoor, 2020) and are highly sensitive to negative experiences and may easily switch brands (Berezina et al., 2012; Sharif et al., 2015). Therefore, it is critical for McDonald's to emphasize product quality and overall-dining experience as these are fundamental to maintain customer satisfaction and loyalty. Additionally, the positive perception of 'Loyalty' within the 'Brand Perception and Loyalty' category indicates that the company has effectively built a loyal customer base, which is crucial for sustaining stream of revenue (Envick, 2021).

However, the analysis also uncovers areas of concern that require strategic focus. Negative sentiment was particularly evident in aspects related to 'Ethical Responsibility' and 'Public Health Impact' under the 'Corporate and Social Responsibility' category, 'Customer Service' within 'Core Restaurant Experience' category, as well as 'Brand Perception' under the 'Brand Perception and Loyalty' category. The negative sentiment surrounding these aspects reveals significant challenges in McDonald's social responsibility initiatives and customer service experiences, which have negatively impacted brand perception. Despite numerous negative perceptions regarding 'Brand Perception', our analysis found a significatn number of positive tweets expressing loyalty towards the brand. This suggests that as Andreassen and Lindestad (1998) argued, although negative perceptions can impact brand image, loyalty is a sperate construct that may be shaped by other factors. Given the speed at which negative word-of-mouth can spread online in today's digital age, effective online reputation management is crucial for businesses (Ismaligova et al., 2020; Javornik t al., 2020).

Companies are increasingly leveraging digital and social media platforms to disseminate information about their services and initiatives to attract support for their causes (Grover, et al., 2019; Hossain et al., 2018; Kapoor and Dwivedi, 2015; Shareef et al., 2016). In the same way, McDonald's should take advantage of its extensive digital marketing channels to foster stronger customer engagement. While McDonald's has expanded its reach through digital marketing (Kumar & Rajan, 2022), targeted efforts are needed to enhance brand's online presence, particularly on platforms like twitter where more than 88% of businesses leverage the platform for their marketing efforts (Lister, 2017).

In today's world, where consumers increasingly prioritize brands that contribute positively to society (Nguyen et al., 2023), McDonald's should align its Corporate Social Responsibility (CSR) efforts more closely with consumer expectation to enhance brand perception. To meet expectations, similar to many companies that strategically communicate their CSR (Crane & Glozer, 2016; Dawkins, 2004; Lock & Schulz-Knapp, 2019), McDonald's can also benefit from the positive impacts of such communications on reputation, brand value, and other key areas (Bhattacharya & Sen, 2004; Yoon et al., 2006; Vierebel, 2022). However, it is important to approach strategic CSR communication with caution, as recipients often view company-provided CSR information with skepticism (Jahdi & Acikdilli, 2009). Concerns about greenwashing can negatively impact the corporate reputation (Du et al., 2010; Eisenegger & Schranz, 2011; Rim & Kim, 2016).

Among the aspects with high negative perception, McDonald's need to address both pricing strategies and customer service quality. Appropriate pricing can enhance customer satisfaction when desired benefits are met, which in turn fosters trust and encourages repeat purchases (Wantrara & Tambrin, 2019). Additionally, as Goofin and Price (1996) highlight, customer service plays a vital role in enhancing product quality, achieving competitive advantage, exploring profitable opportunities, and ultimately boosting sales and revenues. By investing in these areas McDonald's can better meet customer expectations and enhance its competitive position.

In conclusion, while McDonald’s exhibits strength in product quality and customer loyalty, the findings reveal areas of improvement which are essential for the brand to maintain its competitive position. Addressing these issues by the use of digital marketing and digital engagement enables the company to gain a deeper understanding of customer preferences and expectations by strategically collecting and analyzing customer data (Oh et al., 2021). In addition, as Kang (2018) argued, organizations like McDonald's should aim to identify and address the needs of consumers through tailored offerings, which in turn promote engagement and increase satisfaction.

5.3 Limitations of the Study

Limited Labeled Data: One significant limitation was the limited amount of labeled data. Although SMOTE was used to address calss imbalance, the dataset's size may have restricted model's performance.

Single-Platform Focus: The analysis was limited to Twitter data, which may not fully represent public opinion across all social media platform. This platform-specific focus could limit the generalizability of findings.

Dynamic Nature of Social Media: Social media content is constantly evolving, and sentiments can shift rapidly in response to new events and information. Given the dynamic nature of social media and the rapid shifts in sentiment, the findings might not fully capture these shifts in public opinion.

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