Competitive Market Analysis Using Opinion Mining

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Abstract*— In today's everchanging market, understanding feedback from customers on specific product aspects is critical for businesses to stay competitive. Our project, Competitive Market Analysis Using Opinion Mining, applies aspect-based sentiment analysis to deconstruct customer reviews at granular level. By examining sentiments associated with particular product features such as quality, pricing, durability and usability, our approach not only determine overall user emotions but also evaluates the product's performance in these aspects. Harnessing a combination of Natural Language Processing (NLP) and Machine Learning techniques, the project categorizes review sentiments as positive, negative or neutral. While linking them to specific product attributes. This targeted analysis provides valuable comprehension into strengths and weaknesses of the product, allowing businesses to make data-driven decisions and optimize their product's competency in the market. This results in empowering companies to benchmark against their competitors and respond to customer demands effectively.

I. INTRODUCTION

In today's rapidly evolving market landscape, understanding customer opinions and preference is crucial for business to stay competitive. The proliferation of online reviews and social media platforms has transformed the way customers share their experiences and opinions about products. However, the sheer volume and unstructured nature of this data make it challenging for businesses to extract actionable insights. Traditional sentiment analysis methods, which focus on overall sentiment classification, fail to capture the nuances of customer opinions on specific product aspects. This limitation can lead to incomplete and inaccurate market analysis, hindering businesses from making informed decisions. This significance of aspect-based sentiment analysis lies in its ability to uncover nuanced insights into customer preferences and pain points. By identifying and categorizing sentiments related to specific product features, businesses can gain a comprehensive understanding of their strengths and weakness. This granular analysis enables the identification of area for improvement, ultimately informing data-driven decisions to optimize product development and customer satisfaction.

The applications of aspect-based sentiment analysis extend beyond product development and optimization. Our approach can also inform competitive intelligence, market research, and customer experience management. By analyzing customer sentiments across various products and services, businesses can identify industry-wide trends and preferences, ultimately driving innovation and growth. Our proposed approach leverages deep learning techniques to deconstruct customer reviews and evaluate product performance at a granular level. We employ a combination of natural language processing (NLP) and machine learning algorithms to identify and categorize sentiments related to specific product aspects. Our approach enables businesses to identify key product features and their associated sentiments, evaluate product performance across various dimensions, compare products and identify market gaps and also inform product development and optimization strategies. Moreover, aspect-based sentiment analysis facilitates the comparison of products and identification of market gaps. By evaluating product performance across various dimensions, businesses can pinpoint opportunities to differentiate themselves form competitors and address unmet customer needs. This level of analysis is particularly crucial in today's fast-paced market landscape, where customer preferences and trends can shift rapidly.

We demonstrate the effectiveness of our approach through experiments on real-world datasets, showcasing its potential to revolutionize the way businesses interact with customer feedback. Our result highlights the importance of aspect-based sentiment analysis, enable businesses to stay ahead in today's fast paced market landscape. By leveraging the power of deep learning and NLP, our approach provides a comprehensive framework for aspect-based sentiment analysis, empowering businesses to make informed decisions and drive growth. In this paper, we present a detailed overview of our approach, experimental results, and insights into the applications of aspect-based sentiment analysis in competitive market analysis.

II. LITERATURE SURVEY

In [1] This research proposes a review analysis framework for extracting actionable insights from user-generated content to enhance business intelligence. The framework classifies reviews into multiple categories based on their content, such as feature-specific feedback, usability insights, and overall sentiment. Advanced natural language processing (NLP) techniques, including text classification, topic modeling, and sentiment analysis are employed to identify relevant information in each category. The categorized insights are tailored for stakeholders – designers receive data on product improvements, while customers and buyers gain valuable decision – making information. By transforming unstructured reviews into structured, actionable insights, the framework supports strategic decision – making, improving product design and customer satisfaction.

In [2] The purpose of this research is the development of a brand sentiment analysis system which is based on the competing technique of information retrieval and machine learning. The platform's objective is to analyze public sentiment about a brand and be able to outperform the competitors by providing actionable insights. The approach uses textual similarity calculations to process and compare user-generated content; for example, reviews and social media posts, across several competing brands and find sentiment trends. Meanwhile, product similarity, machine learning algorithms, are used for the brand to be competitive in the market as well as product competition. The research promotes easy visualization and decision support tools development to convert complicated data into digestible formats for the users. This study which is a result of combination of these methodologies offers a good framework for real-time tracking of public opinion, thus enabling brands to measure reputation, benchmark against competitors, and refine market strategies.

In [3] This research presents a machine learning – based methodology for sentiment analysis in online product reviews, addressing the growing importance of understanding consumer opinion e-commerce. The proposed approach comprises several key stages: data gathering from online platforms, data preprocessing to clean and normalize textual input, and feature extraction using techniques like TF-IDF, word embeddings, or n-grams to capture semantic and contextual information. Various machine learning algorithm, including Naïve Bayes, Support Vector Machine (SVM) and deep learning models like LSTMs and BERT, are employed to classify sentiments into positive, negative or neutral categories. Experimental evaluations validate the model's robustness, achieving high accuracy in sentiment classification and revealing critical factors influencing customer perspectives. These insights empower businesses to refine product offerings and develop data-driven marketing strategies. As e-commerce evolves, the research provides a scalable framework for leveraging online reviews, enabling enterprises to enhance product quality, customer satisfaction, and competitive positioning.

In [4] This research demonstrates a systematic method to conduct sentiment analysis of online product reviews, applying machine learning aimed at understanding customer positions and tastes. The methodology consists of four important steps, namely: data collection, that collects the reviews from online shopping platforms; data preprocessing, such as noise removal, tokenizing, and normalizing, to let the data be ready for analysis; feature extraction, using techniques like term frequency-inverse document frequency (TF-IDF) or word embeddings to numerically represent textual data; and finally, the machine learning algorithm such as support vector machines, Naïve Bayes, and neural networks for sentiment classification. The accuracy of this method in classifying the sentiments is confirmed by extensive experiments, which also brings to light the principal factors enlightening the consumer attitudes. The insights presented to the companies are actionable and they can use this information to achieve the objectives such as product quality improvement, customer satisfaction, and marketing refinement.

In [5] This research focuses on sentiment analysis of Amazon product reviews using advanced natural language processing (NLP) techniques and neural network architecture. Leveraging a Kaggle dataset of Amazon reviews by Xiang Zhang, the project begins with preprocessing methods, including tokenization, padding, and encoding, to transform raw text into structured inputs suitable for deep learning models. The neural network architecture incorporates bidirectional LSTM layers, which capture contextual dependencies from both past and future sequences of text. Batch normalization ensures faster convergence, while dropout mitigates overfitting. These elements together enhance the model's ability to classify sentiments effectively. Beyond Amazon, the framework demonstrates potential for analyzing user-generated content across domains, contributing to customer feedback analysis, opinion mining, and market research. The model's robust preprocessing and neural architecture hold broader utility for complex NLP tasks, enabling enterprises to extract actionable insights from large – scale textual data and improve decision - making processes.

In [6] This project investigates opinion mining as a tool for enhancing market intelligence by automatically analyzing and summarizing online consumer sentiments. Traditional marketing relied on TV, radio, and print ads to gauge customer reactions, but with the rise o social media, consumers now openly share opinion on platforms like Facebook and Twitter, E-commerce sites, forums and blogs. These sources provide a wealth of unstructured data but also present challenges due to the volume and variety of content. Opinion mining addressing this by analyzing textual data to extract emotions and sentiments from customer feedback, allowing companies to gauge real-time market perceptions without extensive, time-consuming research. This project highlights how opinion mining can support Voice of Consumer (VoC) strategies, helping companies identify customer needs, monitor competitor strengths, and adjust marketing strategies. By using automated sentiment detection and summarization systems, marketers can capture timely insights from customer opinions, thus enabling informed decision-making and improving customer satisfaction and engagement.

In [7] Sentiment analysis or opinion mining is a crucial area of research within natural language processing (NLP) that focuses on identifying and classifying sentiments expressed in digital text, such as reviews, social media posts and blogs. This paper highlights the significance of sentiment analysis in marketing and customer preference research, emphasizing its role in evaluating the effectiveness of advertising campaigns and product feedback. Key challenges sentiments in user-generated content. The research predominantly utilizes two main approaches: machine learning techniques, such as Naïve Bayes, support vector Machines (SVM) and semantic orientation methods, to classify sentiments at document, sentence, or attribute levels. While existing studies mainly focus on English and Chinese texts, there remains a gap in sentiment analysis for languages like Arabic and Thai, signaling opportunities for future exploration in this rapidly evolving field.

In [8] This research undertakes the Aspect-Based Sentiment Analysis (ABSA) for restaurant reviews, which has become a problem with increasing number of online user-generated reviews to analyze. ABSA is impractical for overall sentiment polarity because it is a highly developed form of opinion mining that can measure the sentiment at aspect level. The methodology splits the work into the following three major parts: data collection, in which online reviews about the restaurants are obtained from social media or review sites; data preprocessing, containing jobs such as tokenization, stop-word deletion, and normalization to format data for further analysis; and aspect identification and sentiment classification, where natural language processing (NLP) techniques and machine learning models are used to extract the main aspects (e.g. food, service, ambience) and to find out their empathy depending on the context (positive, negative, neutral). ABSA is a different approach that provides deeper insights through the investigation of review aspects rather than looking at the sentence level.

In [9] This research proposes a robust system for real-time moderation of toxic online content using a multi-featured architecture. The system combines GloVe, Emo2Vec, and BERT to generate rich semantic and contextual embeddings, capturing nuanced meanings and emotional undertones. A BERT-based encoder and classifier detect toxic content, ensuring high precision and contextual accuracy. A rephrasing module transforms toxic inputs into inclusive paraphrases while retaining the core information, fostering constructive dialogue. The system incorporates a reinforcement learning module to adapt and improve dynamically with real-time feedback. This novel approach ensures usability, scalability, and robustness, addressing cyberbullying and hate speech effectively across platforms.

In [10] Semantic Role Labelling (SRL) based on shallow semantic analysis is performed on online product reviews as part of sentiment mining and retrieval system proposed by this study. Specifically, the system extracts meaningful knowledge from consumer reviews by discovering semantic structures and relations. The features it covers include sentiment orientation analysis (i.e. think about a review as positive or negative), and visualizing data of comparative sentiment which provide interpretability and more insights to the humans. Its experimentally validated on a real-world dataset which proves its feasibility and efficiency thereby in capturing nuanced consumer sentiments. With understanding of consumer views being made clearer through this methodology, potential buyers can be better aided in decision-making and businesses may even obtain actionable insights to enhance products and services.

In [11] This research introduces a framework for analyzing opinion formation in online social networks by integrating text mining and swarm intelligence techniques. Text mining processes user-generated content to extract sentiments, topics, and conversational patterns using methods such as natural language processing (NLP) and sentiment analysis. Swarm intelligence models the dynamic interplay of individual influences within the network, simulating opinion propagation based on social relationships and interactions. The system is demonstrated using data from an online gaming community, illustrating how collective behavior shapes opinions. This approach provides actionable insights for market research, enabling a deeper understanding of consumer behavior and social dynamics.

In [12] This study concentrates on the processing of opinions from student feedback through supervised learning algorithms, the data evaluated at the Middle East College in Oman. The methodology is based on machine learning and natural language processing (NLP) technology to find out the polarity of the students' comments which are predefined features such as teaching, learning, and examinations. Data preprocessing, as well as the cleaning and extracting of features, processes the dataset for training. The research uses RapidMiner to execute and assess the algorithms, namely, Support Vector Machines (SVM), Naïve Bayes, K-Nearest Neighbor (KNN), and Neural Networks for classification of binomial sentiment (positive or negative). Every model is measured on evaluation metrics like accuracy, precision, and recall in order to find out the most efficient algorithm for this work. Additionally, the trained models can also forecast the sentiment of the new comments. The comparative analysis shows the pros and cons of each algorithm, which, in turn, helps to find the optimal teaching and learning strategies based on student feedback.

In [13] This research proposes a phrase-level opinion mining system, also known as aspect-based opinion mining (ABOM), for analyzing online customer reviews. The system uses frequent itemset mining to extract product-specific aspects from reviews, enabling finer-grained sentiment analysis compared to document – level or sentence – level approaches. Sentiment orientation (positive or negative) for each aspect is determined using supervised learning algorithm like Support Vector Machine (SVM) or Random Forest, trained on annotated datasets. This approach identifies customer preference and dislikes at an aspect level, providing precise insights for product improvement and marketing strategies. The system is scalable across domains, reducing annotation costs and enhancing sentiment analysis.

In [14] Addresses the influence of online reviews in e-commerce, especially in aiding customers make informed choices and assisting manufacturers with product improvements. It proposes a text analysis method focused on recognizing defective product features by analyzing collection of customer reviews with negative sentiments. By detecting features with recurring negative critique, the system can pinpoint specific product flaws, creating valuable insights for both consumers and producers. For customers, this analysis spotlights potential product issues before making a purchase, while for producers, it provides applicable guidance for improving product quality, ultimately strengthening product development and customer satisfaction strategies on the basis of direct user experiences.

In [15] The evolution of the internet as an interactive platform, emphasizing the weight of customer discussions in Web 2.0 for businesses. It establishes a comprehensive opinion mining framework that employs advanced text mining techniques to automate the extraction, aggregation, and analysis of customer sentiments concerning the products. By implementing natural language processing (NLP) algorithms, the system identifies crucial themes, sentiment polarity, and emerging trends in consumer feedback. This enables the early detection of product strengths and weaknesses, advice product design and marketing strategies. A case study in the automotive sector illustrates the framework's practical application, exhibiting its effectiveness in enhancing competitive edge through data-driven insights.

In [16] This project aims in enhancing decision-making for consumers and entrepreneurs through Aspect-Based Opinion Mining. By examining unstructured user reviews from social networking platforms, it identifies and ranks product strengths and weaknesses. The system processes user reviews through four main stages: Pre-processing, Enhanced Identification, and Opinion Word Extraction using a customized Naïve Bayes model, Aspect Polarity Identification, and finally ranking products and their features. This sequence provides an extensive evaluation of product reviews, enabling faster, more informed purchase decisions and insightful market analysis. Entrepreneurs and analysts can thus leverage consumer opinions to create profitable strategies and understand market trends.

In [17] This research conducts a comprehensive statistical analysis to forecast trends in the global mobile industry, offering valuable insights for consumers, investors, and digital markets professionals. The study focuses on popular mobile device and examines key metrics such as global mobile subscriber growth, market share of leading vendors, trends in operating systems, and the shift from desktop web usage to mobile web. Time-series data was analyzed using Holt's Exponential Smoothing, identified as the optimal model for accurate forecasting of mobile industry trends. Results indicate a significant substitution of desktops by mobile devices in the coming years, underscoring the growing dominance of mobile platforms. The research outcomes provide strategic guidance for investment decisions and support stakeholders in navigating the rapidly evolving mobile market. By predicting market dynamics and consumer behavior, this study equips industry players with actionable insights to remain competitive and align with future digital transformations.

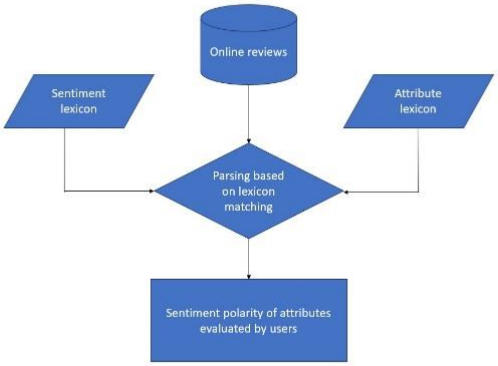
In [18] This research is about WUM, which is a branch of data mining and aims to find data log patterns – hence, web log data's meaning and significance can be obtained. WUM works with the huge data sets that are uploaded to the site by many users to view optimal web application and to analyze the user behavior. The process is structured into four stages: data sourcing, which involves collecting web log data; preprocessing, where raw logs are cleaned and structured for analysis; pattern identification, which applies algorithms to detect behavioral patterns; and pattern analysis, which interprets these patterns to derive actionable insights. The plan of website usability improvement by web log analysis will ne used in educational institutions to attract new and retain current users. Through the study of user navigation and interaction trends, the research is to explore the area of user satisfaction and application performance.

In [19] This research focuses on enhancing retail operations and customer experience through "Market Basket Analysis for Retail Sales Optimization", leveraging advanced association rule mining algorithms – Apriori, FP-growth, and Eclat. Using a rich dataset of historical transaction records, the system uncovers patterns, correlations, and frequent itemsets to recommend items often purchased together. The Apriori algorithm identifies association rules by iteratively finding subsets of frequent itemsets, while FP-growth avoids candidate generation by leveraging a compact data structure called the FP-tree. Eclat employs a vertical database representation for efficient mining. These techniques ensure scalability and precision in analyzing large transactional datasets. The insights derived are applied to optimize store layouts by placing frequently bought-together items in close proximity, facilitating ease of access and encouraging additional purchases. This data approach enhances the shopping experience and drives sales growth. The research bridges data analytics and retail strategies, offering an innovative and scalable framework for retail sales and customer satisfaction optimization.

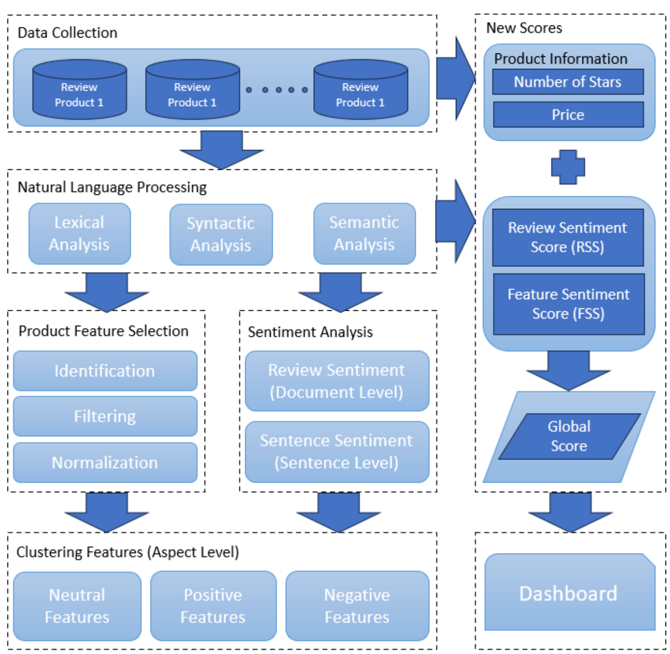
In [20] This research propose a hybrid framework for sentiment analysis on social networking sites, combining Convolutional Neural Network (CNNs) for feature extraction and Support Vector Machine (SVMs) for classification, augmented with trend analysis. The study uses a labeled Twitter dataset (positive, negative, neutral) to identify trending topics and track shifts in public opinion. The CNN component extracts hierarchical features from textual data, capturing both global and local patterns, and encodes semantic and contextual nuances of the tweets. These features are passed to an SVM classifier, which leverages its strength in high-dimensional spaces to achieve precise sentiment classification. Trend analysis enhances the interpretability of the results by identifying temporal patterns and emerging topics. Experimental results demonstrate that the CNN-SVM hybrid model outperforms traditional methods in accuracy, precision, and recall, proving its robustness in diverse linguistic and thematic contexts. This methodology provides a scalable and interpretable solution for sentiment analysis across social media platforms.

III. PROPOSED METHOD

Opining mining, also known as sentiment analysis, is a subdomain of natural language processing (NLP) that concerned with receiving subjective information from textual data to identify sentiment, emotions, or opinions. It entails computational methos of recognizing and sorting opinions that are being expressed into categories such as product reviews, social media posts or feedback forms, thereby allocating them to positive, neutral or negative groups. The primary operation of opinion mining, thus, is based on the use of machine learning algorithms, lexicons-based approaches and hybrids method Opinion mining that is based on machine learning methods uses supervised and unsupervised learning models to classify the content of the document. Supervised models, for instance, are Naïve Bayes, SVMs or neural network and they need labeled datasets for training in order for the algorithm to learn the patterns tied to particular sentiments.



In contrast, the lexicon-based methods employ the predefined dictionaries that associate positive and negative words with sentiment in order to input the score of the sentiment through the calculation of the score. Viscerally, deep learning models like LSTM and transformer architecture utilizing BERT, GPT, and other architectures have significantly aided in the opinion mining sector by capturing contextual dependencies and semantic nuances, despite the fact that this part is often the most difficult. Preprocessing means performing tasks such as tokenizing, stemming and eliminating words that don't add meaning. Post-processing, which may involve aggregation techniques to represent the collective choices, is the next step therefore organizations can intelligently solve the problem by looking for patterns in the data that they now accumulate thanks to this development.



Aspect-Based Sentiment Analysis (ABSA) is a differentiated method of Natural Language Processing (NLP), which extracts and analyzes the sentiment for specific aspects or features of a product along with the customer reviews. The method facilitates a deeply granular analysis by the attribution of specific sentiment scores (e.g. positive or negative) to relevant product features of quality, pricing, durability, and usability. The core of this targeted sentiment scoring is competitive analysis because of the data in which it reports the findings that general sentiment analysis might not cover.

Process flow in Aspect-Based Sentiment Analysis:

1. Aspect extraction: The operation starts from identification of the aspects related to each review. For aspects like price, quality, design, and durability might be detected. By using NLP techniques such as keywords extraction, part-of-speech (POS) tagging, dependency parsing, or topic modelling are the things that help to isolate these target features from the text.

2. Sentiment classification: The extraction of aspects is followed by sentiment analysis that assesses how unfavorable or positive the expressed opinion about aspects is. In this case, classifiers such as Support Vector Machines (SVM), Naïve Bayes, or the latest models such as Bidirectional Encoder Representations from Transformers (BERT) or Long Short-Term Memory (LSTM) networks may be applied to ascertain whether the sentiment is positive or negative.

3. Polarity and Score Calculation: For competitive analysis, Sentiment scores are further divided into grades of meaning, the first one being negative (0) and the other being positive (1), or larger ranges of values that lie between 0 to 1 according to model sophistication. This process allows to measure each issue more accurately by extracting data from numerous reviews, hence obtaining averages or sentiment distributions that are wider sentiments of customers.

4. Aspect-Specific Aggregation: For marketing, aggregated sentiment scores per aspect are compared across similar products. This allows a side-by-side comparison of how competing products are perceived in terms of specific attributes, highlighting where a product excels or falls short.

5. Visualization and Insights: Visualizing sentiment distributions per aspect using charts and dashboards provides businesses with a comprehensive view of product strengths and weaknesses. With these insights, companies can benchmark against competitors, identify unique selling points and refine product positioning based on customer feedback.

A. Bidirectional LSTM (BiLSTM):

The BiLSTM model is one of the most suitable choices for the Aspect-Based Sentiment Analysis (ABSA) as it has the capability to capture sensitive information from the temporal spectrum of words in a sentence. A sentiment analysis at aspect level is the task of subjectivity or opinion mining with respect to different aspects of an entity (e.g. battery life or display quality in a mobile review). LSTM is an RNN that solves the vanishing gradient issue seen in RNNs. Its architecture makes it possible for long-term dependencies to be learned. In a Bi-directional Long Short-Term Memory (BiLSTM) model, two LSTMs are employed; the first one reads the sentence from beginning to end (forward) while the second one reads the sentence from end to beginning (backward). This bidirectional approach allows the model to grasp dependencies from both directions, which is especially useful when determining sentiment that depends on surrounding context. For ABSA, the model first identifies aspects in a sentence. Then, using word embeddings like GloVe or BERT to represent each word as dense vector, it processes the sentence through the BiLSTM layers. Each LSTM layer captures different aspects of the context for each word. Finally, a fully connected layer and softmax function classify the sentiment (e.g. positive or negative) toward each identified aspect, giving an aspect-specific sentiment output. This setup enables the model to perform fine-grained sentiment analysis efficiently.

B. Convolution Neural Network:

A Convolutional Neural Network (CNN) model for Aspect-Based Sentiment Analysis (ABSA) leverages convolutional layers to identify sentiment-related patterns within localized text regions for specific aspects in a sentence or document. The process begins with input representation, where the text is tokenized and converted into word embeddings using techniques like Word2Vec, GloVe or BERT embeddings. These embeddings capture the semantic meanings of words and form a 2D matrix, with each row corresponding to a word vector in the sentence. This structured representation sets the foundation for subsequent layers in the CNN architecture. The Convolutional layer applies filters (or kernels) to the word embedding matrix. These filter slide over the input embeddings to capture matrix. These filters slide over the input embeddings to capture sentiment-related n-grams, such as “good battery” or “poor display”. Each filter detects specific patterns within a fixed window size, which helps in identifying sentiment cues near the aspect in focus. The output of this operation is a feature map, where each value represents the strength of a particular sentiment feature within the local context of each aspect. After convolution, a pooling layer is employed, typically using max – pooling, which reduces the dimensionality by retaining only the most relevant sentiment features. This pooling step enhances the model’s robustness to positional variations in words, allowing it to concentrate on the strongest sentiment indicators. Finally, the pooled features are flattened and passed through one or more fully connected layers. These layers enable the model to learn complex patterns across different aspects. The process concludes with a classification layer, often using softmax or sigmoid activation, which outputs the sentiment polarity (e.g. positive or negative) for each aspect in the text. Through this architecture, CNNs effectively capture sentiment-relevant patterns for ABSA, particularly by focusing on localized dependencies specific to each aspect.

C. Tokenizer:

A tokenizer is a crucial component in natural language processing (NLP) that transforms raw text into a structured format suitable for machine learning models. Its primary function is to split text into smaller units called tokens, which can be words, sub-words, or characters. The tokenizer process typically involves several steps. First, the input text is normalized through processes like lowercasing, punctuation removal, and whitespace handling. Next, the tokenizer identifies boundaries between tokens, which may involve using regular expressions or predefined rules. In word-based tokenization, each distinct word becomes a token, whereas sub-word tokenization techniques, like Byte Pair Encoding (BPE) or WordPiece, break down words into smaller, meaningful subunits. This is particularly beneficial for handling out-of-vocabulary words and reducing the vocabulary size by creating a dynamic token set from frequently occurring word segments. After tokenization, each token is mapped to a unique integer ID using a vocabulary dictionary, which allows the model to process textual data numerically. Furthermore, many tokenizers also handle special tokens, such as [CLS] for classification tasks or [SEP] for separating segments in tasks like question answering. The final output of a tokenizer is typically a sequence of token IDs, along with attention masks and segment IDs, if required. This structured representation is then fed into models, such as Transformers, to perform various NLP tasks effectively, enabling the model to understand and generate human language.

D. Ensemble of BiLSTM and CNN

In this ensemble model combining BiLSTM and CNN for Aspect-Based Sentiment Analysis (ABSA), Initially, it involves processing the input text and creating word embeddings. Each sentence is broken down into individual words, which are then transformed into dense vector representations using embeddings such as Word2Vec, GloVe, or BERT. These embeddings represent each word in a high-dimensional space, capturing semantic similarities and relationships between words. This step is critical as it allows the model to understand the meaning of words and their interrelations within the sentence, providing a strong basis for subsequent analysis. For ABSA, it is often necessary to identify the specific aspect within a sentence, such as battery life or display quality in a phone review, either manually or through an automated process. Many ABSA models use part-of-speech tagging or separated aspect extraction models to detect these aspects. Once identified, these aspects aid in directing the sentiment analysis process by narrowing the model’s focus to relevant parts of the sentence. This targeted approach ensures that sentiment is analyzed in relation to each aspect, enhancing the model’s performance.

For a sentence $X = [W_1, W_2, \ldots, W_n]$, the embeddings are:

$$X = [E(W_1), E(W_2), \ldots, E(W_n)]$$

Where $X \in \mathbb{R}^{n \times d}$ and d is the embedding dimension.

After embedding, the input vectors are passed through a Bidirectional Long Short-Term Memory (BiLSTM) layer to capture sequential context. The BiLSTM layer processes the embeddings in both forward and backward directions. The forward LSTM parses sentence from start to end, while the backward LSTM parses it from end to start. This bidirectional approach is particularly beneficial for understanding how the surrounding words impact the sentiment of a given aspect. For example, the model can detect that “not” before “good” negates the positive sentiment of “good”, which is critical for accurate sentiment classification.

Let h_i^{fwd} and h_i^{bwd} be the hidden states at position i from the forward and backward LSTM, respectively. The combined output at each position i is:

$$h_i^{BiLSTM} = [h_i^{fwd}, h_i^{bwd}]$$

So, the BiLSTM output for the sentence is:

$$H^{BiLSTM} = [h_1^{BiLSTM}, h_2^{BiLSTM}, \ldots, h_3^{BiLSTM}]$$

Where $H^{BiLSTM} \in \mathbb{R}^{n \times 2h}$ and $2h$ is the hidden dimension size.

In parallel, the input embeddings are fed into a Convolutional Neural Network (CNN) layer. Here, the CNN applies multiple filters to capture local patterns or n-grams, such as phrases like "very satisfied" or "poor quality", that are associated with sentiment. Let Fk be a filter with size k. The feature map generated by Fk at position i is $c_i^{(k)} = f(W_k \cdot x_{i:i+k-1} + b_k)$, where W_k and b_k are the weights and bias for the filter, and $f(\cdot)$ is a nonlinear activation function (e.g. ReLU). The output from each filter is pooled, resulting in $C^{CNN} = [c_1^{(k)}, c_2^{(k)}, \ldots, c_m^{(k)}]$, where $C^{CNN} \in \mathbb{R}^m$ (after pooling), with m filters applied. The CNN excels at detecting these local features and spatial patterns within fixed-length sequences, allowing it to recognize sentiment-laden phrases effectively. By applying multiple filters, the CNN can detect patterns that may be overlooked by BiLSTM alone, adding depth to the model's understanding of sentiment cues. The outputs from the BiLSTM and CNN layers are then concatenated to form a unified feature representation. This combined output integrates the sequential context from the BiLSTM with the local feature detection from the CNN, providing a richer representation of the input sentence. This integration about each word and aspect, enhancing its ability to discern subtle sentiment nuances that are essential in ABSA.

Finally, the concatenated features are passed through a fully connected layer to produce sentiment scores for each aspect, $z = W \,.\, H^{combined} + b$, where W and b are the weights and bias of the fully connected layer, followed by a softmax function, which classifies the sentiment for each aspect as positive, negative or neutral $(y^{aspect} = softmax(z))$. The fully connected layer maps the complex features generated by the ensemble to specific sentiment classes, completing the aspect-based sentiment classification process. This model outputs the predicted sentiment for each identified aspect, enabling fine-grained analysis across different aspects in a sentence or text. By combining the contextual insights from BiLSTM with the CNN's pattern recognition capabilities, the ensemble model achieves greater accuracy and robustness, effectively capturing both contextual dependencies and essential sentiment phrases for ABSA.

IV. RESULT AND DISCUSSION

The dataset used for this aspect-based sentiment analysis project consists of balanced product reviews, which contain a total of 5,300 entries. Each entry includes a text review and labels indicating sentiment for specific aspects within the review. The balanced nature of the dataset ensures that each sentiment category positive (1) or negative (0) is well-represented, minimizing the risk of model bias toward any particular sentiment class. This diversity and balance in the dataset make it suitable for training and evaluating models, as it allows them to generalize well across different sentiments and aspects.

Using contextual patterns acquired from the training dataset, the system efficiently categorizes reviews as either positive or negative for particular product features. Through the examination of sentiment expressions pertaining to characteristics, quality, or price, the model finds terms and expressions that reflect sentiment polarity. Based on the text's context, the model effectively predicts sentiment classifications on test reviews after training, correctly differentiating between positive and negative feedback.

The final output for each aspect is:

$$Y_{aspect} = \textit{Sentiment Label} \in \{\textit{positive or negative}\}$$

The choice of models for this project was guided by the need to capture both local and sequential patterns in the text, as aspect-based sentiment analysis requires understanding specific words (local patterns) and context (sequential dependencies). Traditional models like CNN and BiLSTM are well-suited for tasks. CNNs excel at detecting local patterns in data, making them effective for identifying sentiment-related keywords or phrases. However, CNNs are limited in capturing context over long text sequences, which is crucial for sentiment analysis, where meaning often depends on word order.

To address the limitations of CNNs, we also employed BiLSTM model, which is designed to capture sequential dependencies. BiLSTM can learn long-term dependencies by processing the text in both forward and backward directions, making it well-suited for understanding the context of each word in relation to others in the sequence. However, BiLSTM alone may not fully capture the local features, which led us to explore ensemble models.

In the aspect-based sentiment analysis project, multiple models were evaluated to determine the most effective approach for accurately classifying sentiments. The models tested include individual deep learning models, such as CNN and BiLSTM, as well as transformer-based models like BERT. Additionally, ensemble models combining BiLSTM with CNN and BiLSTM with BERT were explored to enhance performance by leveraging complementary strengths.

The Ensemble model (BiLSTM + CNN) trained over 10 epochs achieved the highest overall performance, with an accuracy of 98.11%, precision 99.73%, recall of 0.9649, and F1-score of 0.9808. this indicates that the ensemble benefits from the CNN's ability to capture local patterns (useful for detecting specific keywords or aspects in sentiment analysis) combined with BiLSTM's capability to capture sequential dependencies, making it highly effective for this task. The extended training of 10 epochs likely contributed to this model's superior performance by allowing it to learn complex patterns more effectively.

The BERT model, trained for 3 epochs, achieved strong result as well, with an accuracy of 95.27% and F1-score of 0.9527. BERT's transformer-based architecture enables it to capture nuanced semantic relationships in text, which is crucial for understanding the sentiment associated with different aspects.

However, its performance falls slightly short of the BiLSTM + CNN ensemble, possibly due to the limited training duration. Furthermore, epochs might improve BERT's performance, as it typically benefits from more extensive training on fine-grained task.

The Ensemble model (BiLSTM + BERT) achieved an accuracy of 90.38% and F1-Score of 0.9052. Although this model utilizes BERT's contextual understanding and BiLSTM's sequential modelling capabilities, it didn't perform as well as the BiLSTM + CNN ensemble. This may be due to challenges in effectively combining the transformer-based BERT model with BiLSTM, as they may not complement each other as seamlessly as CNN and BiLSTM.

The standalone BiLSTM and CNN models, trained for 3 epochs, showed relatively lower performance, with accuracies of 88.49% and 85.28%, respectively. BiLSTM achieved a slightly higher F1-Score of 0.8794 indicating its stronger performance compared to CNN in capturing sequential dependencies. CNN's performance, with an F1-Score of 0.8500, suggests it may struggle with more complex sentiment patterns without additional context provided by sequential modelling.

Performance analysis of evaluated models:

Standalone models:

Model	**Accuracy (%)**	**Precision (%)**	**Recall**	**F1 Score**
BERT	95.2652	95.3603	0.9527	0.9527
BiLSTM	88.4900	86.5800	0.8936	0.8794
CNN	85.2800	85.0000	0.8500	0.8500

Ensemble models:

Model	**Accuracy (%)**	**Precision (%)**	**Recall**	**F1 Score**
BiLSTM × CNN	98.1125	99.7269	0.9649	0.9808
BiLSTM × BERT	90.3800	90.8600	0.9019	0.9052

Full models' summary table sorted by accuracy in descending order:

Model	**Accuracy (%)**	**Precision (%)**	**Recall**	**F1 Score**
BiLSTM × CNN	98.1125	99.7269	0.9649	0.9808
BERT	95.2652	95.3603	0.9527	0.9527
BiLSTM × BERT	90.3800	90.8600	0.9019	0.9052
BiLSTM	88.4900	86.5800	0.8936	0.8794
CNN	85.2800	85.0000	0.8500	0.8500

V. CONCLUSION

In conclusion, this aspect-based sentiment analysis project demonstrates the effectiveness of combining deep learning and transformer models for complex NLP tasks. By exploring different architectures, including CNN, BiLSTM, BERT and various ensemble models, we achieved valuable insights into how each model captures different aspects of sentiment within text. The BiLSTM + CNN ensemble model emerged as the best-performing model, achieving a high accuracy of 98.11% and F1-score 0.9808. This success underscores the advantages of leveraging CNN's local pattern recognition and BiLSTM's sequential context understanding, resulting in a model well-equipped to detect aspect-specific sentiments accurately. Although BERT and the BiLSTM + BERT ensemble also showed strong performance, they did not outperform the BiLSTM + CNN ensemble within the constraints of this project.

This project illustrates the potential of ensemble approaches in aspect-based sentiment analysis, particularly when complementary models are combined. The findings suggest that future work could further optimize these models, potentially increasing BERT's performance with longer training or fine-tuning strategies. Overall, the project establishes a solid framework for sentiment analysis in product reviews, which can be expanded for more complex, real-world applications.

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