

Decoding Customer Sentiments: A Dashboard-driven Solution for Product Comment Analysis

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Abstract: In the rapidly changing e-commerce landscape, businesses need to use the most advanced analytics technology to gain competitive advantage and meet customer needs. Our search starts with traditional methods such as NLTK + TextBlob and VADER, which provide a stable baseline with an accuracy of 73.99% (F1 66.01%) and 67.35% (F1 54.46%), respectively. However, in search of a deeper understanding, we chose Word2Vec, which uses single word embeddings to capture relationships, achieving 80.01% accuracy (F1 79.56%), making the hypothesis clear. The LSTM model, known for its connectivity pattern recognition, showed 69.95% accuracy (F1 66.35%), but its performance paled in comparison to Transformer-based architectures. Among them, BERT achieved 68.57% (F1 73.93%) accuracy despite the challenges of computing resources and good knowledge training, changing the perception of user feedback and analysis. However, the undisputed winner in determining user sentiment, surpassing all other models with an impressive 97.70% accuracy and 86.21% F1 score, is the BiLSTM model, which refers to the use of technology to create content and gather opinions from users to increase traffic. The importance of providing useful feedback to customers, business success and e-commerce growth.

Keywords: Product Comment Analysis; Dashboard Visualization; Customer Sentiment; E-commerce; Data-driven Decision Making; Customer Feedback; Text Analysis

1. Introduction

The dynamic world of e-commerce is developing in line with people's needs. While positive feedback can move a brand forward, negative feedback can hinder a purchasing decision. According to research, 4.75 billion content is shared on Facebook every day and 510 messages are sent every 60 seconds [1]. These online customer reviews have become an important source of information that has a huge impact on customer choice and sales. According to Gartner, 67% of consumers say they are influenced by online reviews and are as likely to trust them as they are to trust personal recommendations [2]. While there is so much data, there is also a need for a process that can be analyzed if the methods used in these studies are related to new production and can give an idea about which methods should be used for future

projects, process and analysis. Ideas obtained from the analysis of existing products. The analysis should be used as important information for consideration by decision makers and product planners of small and medium-sized enterprises [3]. Many researchers believe that the manufacturing industry has become a customer-focused organization whose success depends on understanding the customer's needs. Therefore, understanding why customers make their decisions is as important as understanding how much they enjoy the product. This is a difficult problem for marketers and psychologists [4,5]. To change the situation and meet customers' needs, businesses need the right sentiment analysis tools. In data analysis, dashboards are important tools that provide a comprehensive view of complex data in an intuitive way. It allows stakeholders to monitor performance, identify opportunities and make informed decisions. Dashboards use interactive charts, tables, and indicators to help you quickly understand trends, patterns, and trends in different areas. Research on the use of dashboards demonstrates the diversity of design goals, levels of discussion, and applications. Qualitative analysis of the data establishes the design environment of dashboards, identifies the main types, and shows the results of research recommendations to improve design, implementation, and use [46]. Additionally, the empirical study demonstrates the key features, uses, and advantages of performance dashboards. Research results show that dashboards serve many purposes, from monitoring to communication to relationships, and are successfully associated with customer productivity and management [47]. As interest in dashboards grows, organizations are trying to gain insight into their results. A comprehensive literature review revealed important issues in dashboard implementation, highlighting the importance of visual content, features such as flexibility, and feedback-based approaches recommended for a good dashboard design [48]. Additionally, it has been revealed that the design process guides the development of dashboards in business management regarding the combination of graphics and study to achieve effective solutions [49]. But there are still challenges in creating effective dashboards for business intelligence (BI) purposes. While BI dashboards provide valuable support for data visualization, performance management, and monitoring, organizations still struggle to select and design dashboards that support data-driven decision-making. An extensive literature review and interviews with experts found problems in the use of business intelligence and suggested activities and features that improve decision making [50]. Dashboards are, at their core, analytical tools that provide stakeholders with a clear, concise and actionable view of complex data. From performance monitoring to decision making, dashboards enable organizations to analyze complex data, optimize resources, and stay ahead of the curve by predicting changes. Thanks to continuous research and development, the ability of dashboards to drive strategic decisions continues to expand, promising deeper insights and better performance in many places.

Opinion mining, also known as opinion research (SA), is the evaluation of people's beliefs, attitudes and opinions about a topic. Objects can represent a person, object, or subject [6]. In recent years, emotional assessment has become increasingly popular in education. A number of theory research papers provide an overview of theory mining in its early stages [7]. There is more to emotional observation than meets the eye. Generally speaking, emotions are more important than feelings, but emotions play an important role in our lives, and one of the basic characteristics of humans is the ability to express thoughts and feelings in words. Emotions, or expressions of emotion, may include two additional categories, the researchers said. First, decisions are shared with others; Secondly, pleasure or aesthetic feeling is expressed. Emotional analysis examines how we express our thoughts and feelings and organize them through affect, judgment, and interest. The emotional evaluation process has many difficulties, one of the main problems is speech, which is the main problem encountered in the emotional evaluation stage (9). Emotional analysis can also be effective as a combination of other systems. They can increase the efficiency of the deal and customer relationship management [10]. For this reason, emotional analysis is also used for product analysis. However, for some reason it is not as easy as it seems. This process is quite difficult due to the complexity of human language. There are many grammatical and cultural variations. Therefore, emotional analysis sometimes needs to be done specifically to make correct judgments [11]. One researcher used the NRC's emotional expressions to describe consumers in two emotions (positive and

negative) and eight behaviors (anger, fear, trust, hope, sadness, surprise, disgust, and joy) [12]. Many studies claimed that there were three main problems in applying sentiment analysis on product reviews:

- User reviews of a product are regarded as favourable in certain circumstances and negative in others.
- Positive and negative feedback will typically be included in reviews, which can be handled to some extent by breaking down each statement in turn.
- Occasionally, individuals may post fictitious reviews of the goods, leading to negative perceptions of it [13].

2. Materials and Methods

Sentiment analysis has become a powerful technique in ongoing research to gain insight from customer feedback and understand what customers think about a product or service. This research involves in-depth evaluation and application at all stages, from data collection and preprocessing to theoretical analysis, data exploration, visualization, and interpretation. In this study, we used the data set on the data.world website. The database has more than 30,000 reviews from brands such as OnePlus and Redmi. All reviews are presented in JSON format and include details about customer thoughts and opinions about each brand. This database is very useful for analyzing products using sentiment analysis techniques. By summarizing the opinions expressed in reviews, insights can be gained about customer satisfaction, product strengths, areas for improvement, and general understanding of the products. We have created a detailed guide that will serve as a guide for the entire process.

The flowchart below demonstrates the steps involved in conducting a robust product review analysis.

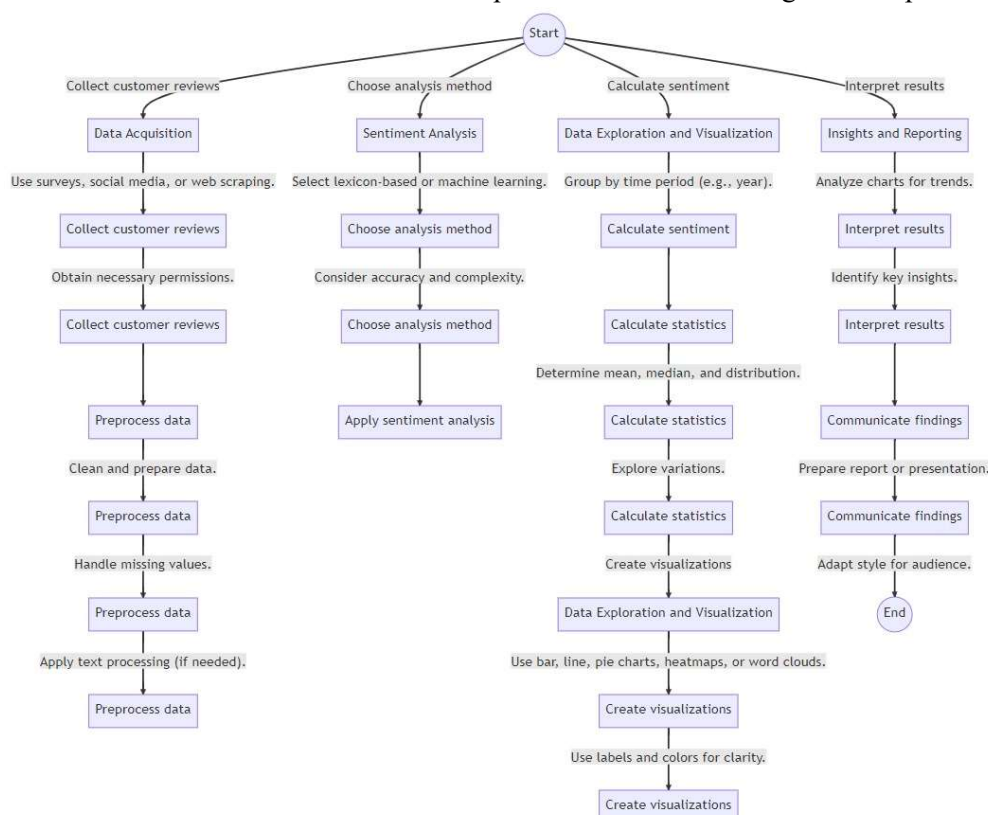


Figure 1. A Flowchart Diagram of Generalized Method of Algorithm Implementation

To clearly understand the flowchart given below are key details of the stages of the flowchart:

- **Data Acquisition:** The first step in the process is to collect customer reviews, which can be done through a variety of methods such as surveys, social media, or web scraping. This is a delicate stage because it determines the quality and quantity of the product. Approval from relevant organizations is also required to comply with data privacy laws.

- **Preprocessing:** After receiving the customer's ID, the next step is to prepare the data. Preprocessing of data sets includes routine cleaning and data preparation by handling missing values. Word processing includes tokenization, stemming, lemmatization, word removal, etc. where necessary. may include transactions. This stage cannot be ignored because it ensures that the data is in a format suitable for analysis and increases the accuracy and reliability of the data.
 - **Sentiment Analysis:** The main structure of the product review process is sentiment analysis, whose purpose is to calculate and classify opinions in customer reviews. There are two main ways to analyze emotions:
 1. **Lexicon-based Methods:** Dictionary-based methods rely on pre-emotional annotations that label words or phrases associated with positive, negative, or neutral emotions. This method generally works by counting the number of positive and negative words appearing in the text and calculating the total score of the thought based on calculation and preliminary weighting.
 2. **Machine Learning-based Methods:** On the other hand, machine learning-based methods analyze sentiment by training on samples of registered customer review articles. This model learns to classify new teachers' opinions based on patterns and characteristics observed in new feedback patterns in teaching materials. Commonly used machine learning algorithms for hypothesis testing include support vector machines, naive Bayes, and deep learning models such as neural networks and transformers.
 - **Data Exploration and Visualization:** After using the method of choosing thought theory, the next step is to investigate and see the results. This usually means taking data over time (such as years) and calculating various statistics such as mean, median, and distribution of emotional scores.
 - **Visualization Techniques:** A variety of visualization techniques such as line charts, graphs, line diagrams, heat maps, or word cloud can be used to effectively communicate research. These visualizations can help you identify trends, patterns, and key insights in the data. It is important to use appropriate text, colors and images for clarity and ease of interpretation.
 - **Insights and Reporting:** The final stage of the process involves visual analysis and graphs to identify key insights and patterns in the product analysis that can be found in product analysis reports. This information may be used to inform product development, marketing strategies or customer service.
- By following this approach, researchers and analysts can use analysis theory to make the most of customer reviews, ultimately leading to informed decisions and improved products.

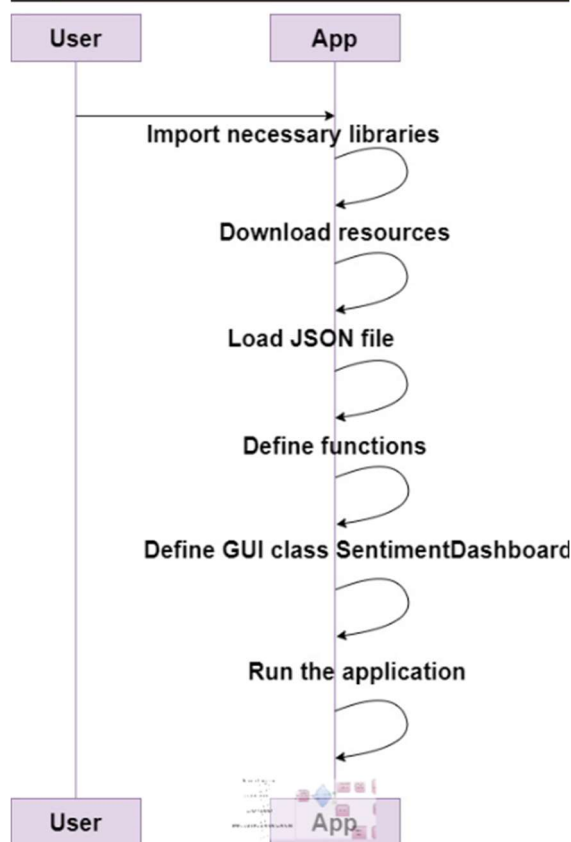
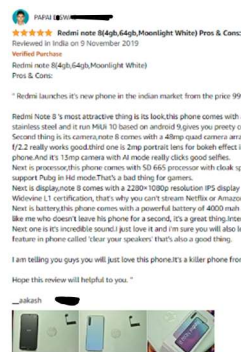
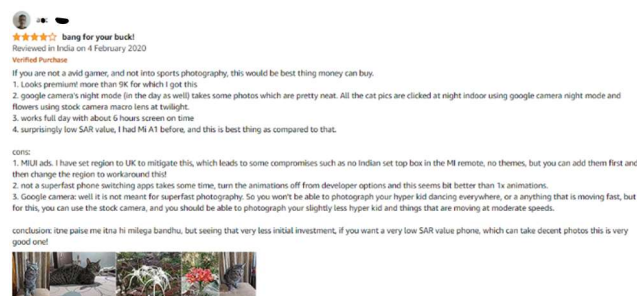


Figure 2. Flowchart of General Code Implementation of Dashboard

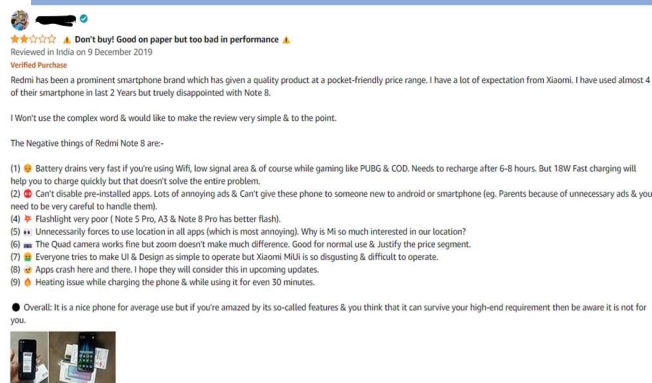
This flowchart walks you through the process of creating a sentiment analysis dashboard. Start by deploying the appropriate libraries and downloading resources as needed. A JSON file containing the search query data is then loaded. The next step involves defining the tasks and other capabilities required for analysis. The core of the process is the definition of a GUI class called "sentiment_dashboard()"; this makes it possible to create a graphical user interface for a sentiment analysis dashboard. Finally, the entire application can display a view of the analytics dashboard for user interaction and analysis. In general, this flowchart contains sequential steps from planning to execution of a control panel application.



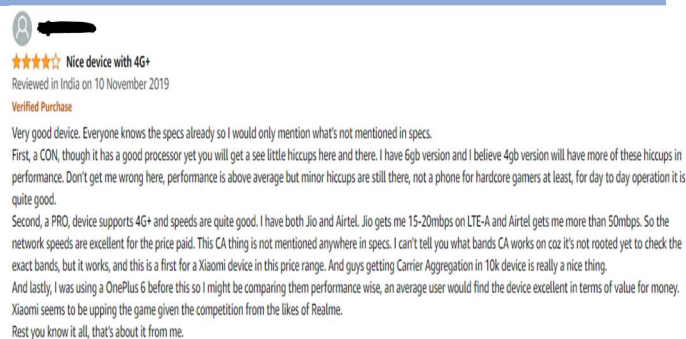
(a)



(b)



(c)



(d)

Figure 3. Example for Reviews of Phone Redimi Note 8: (a); (b); (c); (d) Images of real Amazon Reviews on the Product “Redimi Note 8”. As seen the customers clearly state the advantages and disadvantages of the phone. This gives the manufacturers a clear idea of their areas of improvement for the future phone by analyzing the current phone reviews. Such a huge amount of data is not easy to comb through. Thus enters the reason for our experiment on dashboards for product analysis where data like the above can be taken and given to such dashboard.

2.1 Textual Analyzer using NLTK + TextBlob Algorithm

NLTK, together with TextBlob, provides a simple yet effective method for sentiment analysis, making it an attractive choice for many NLP tasks. Although it lacks the intelligence and expertise of models such as BERT, this method stands out for its simplicity and speed, making it suitable for situations where rapid analysis and detailed understanding are more important. This implementation involves the use of NLTK for text preprocessing and TextBlob for polarity analysis [22].

NLTK (Natural Language Toolkit) provides libraries and tools for language processing, including tokenization, stemming, and blockword removal. Using the capabilities of NLTK, data files can be pre-processed to remove noise and remove important features, ensuring good performance when analyzing emotions.

TextBlob is a simple text processing library based on NLTK and provides easy integration for a variety of NLP tasks, including sentiment analysis [21].

The process of sentiment analysis using NLTK + TextBlob starts with the initial data where written words are cleaned and put into words or tokens. Each tokenized comment is then passed through TextBlob's sentiment analysis, which assigns a polarity score (positive, negative, or neutral) representing sentiment. The polarity score is determined by the presence of positive or negative words in the text, using a threshold to define the boundaries of each group of thoughts [23].

The implementation of sentiment analysis using NLTK + TextBlob involves several key steps, each contributing to the overall functionality of the system.

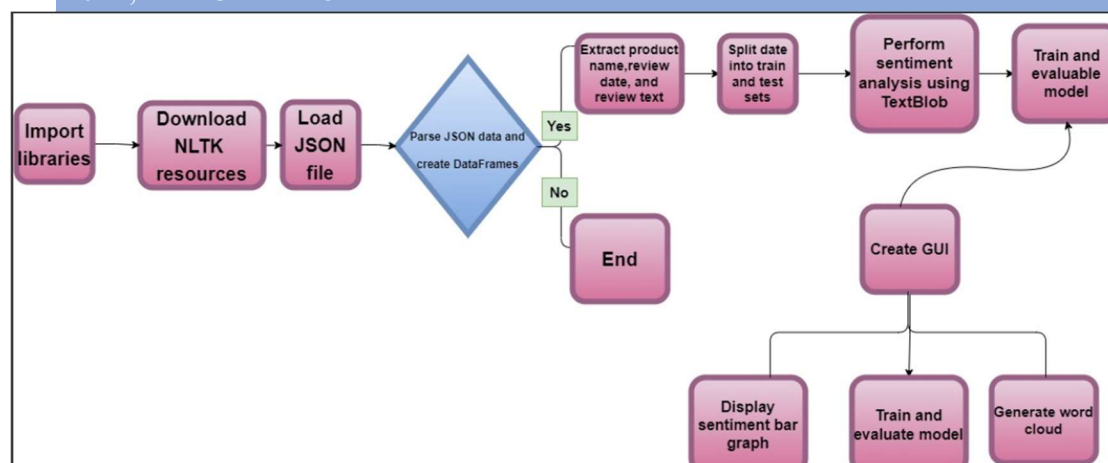


Figure 4. Flowchart of Code Implementation of NLTK + TextBlob Algorithm

This flowchart describes the emotional analysis of reading materials. First you need to import the library and download the NLTK resources for the NLP project. Item names, review dates, and tags are extracted from JSON files that are loaded, parsed, and organized into data frames. The data is divided into testing and training sets. TextBlob is used for sentiment analysis and training and evaluating models. The GUI displays the results and shows the export purpose using a bar chart. The model was further developed to create a word cloud suitable for content analysis. This systematic approach enables emotional assessment, supports intuition-based decision making, and allows for prior knowledge and insight.

- Initial data and upload: The first steps involve uploading a file containing the analysis object stored in JSON format. To facilitate further analysis, reviews were extracted and placed into data frames for each item. All reviews include text and relevant dates.
- Sentiment Analysis with NLTK + TextBlob: Sentiment analysis using NLTK and TextBlob libraries. All comments are analyzed for sentiment using the TextBlob sentiment analysis module. TextBlob provides a polarity score that represents sentiment (positive, negative, or neutral) based on the presence of positive or negative words in the text.
- Calculation of opinion percentage: The next step after opinion analysis is to calculate the opinion percentage for each opinion group (good, negative, moderate). This process requires repeating the message and counting the number of occurrences of each thought tag. Then, use all the words to determine the percentage of each set of thoughts.
- Creating a Sentiment Analysis Dashboard: The dashboard is designed to provide users with information about sentiment analysis in product reviews. It provides three main functions:
 1. Visual analysis: Users can use graphs to visualize wiring. These charts show the percentage of good, bad, and average reviews for each product, allowing users to quickly understand their need to take care of different things.
 2. Word cloud creation: The dashboard helps create a word cloud that shows the most common words in the word. These features help users understand all the ideas and content discussed by providing information about the key concepts and topics discussed in the message.
 3. Accuracy evaluation: Users can evaluate the accuracy of sample requirements directly from the control panel. By training the model and calculating metrics such as accuracy and F1 score, users can evaluate the model's performance in opinion classification and provide useful feedback on confidence in survey results.

Overall, this application uses the simplicity and efficiency of NLTK + TextBlob for sentiment analysis, providing solutions for analyzing text files and eliminating perspective.

Although simple and fast, NLTK + TextBlob may exhibit limitations in performance. Identify negative emotions with high accuracy. Failure to recognize negative emotions such as sarcasm or irony can lead to negative emotions, affecting the overall accuracy of the analysis. Additionally, relying on lexical analysis and prioritization techniques to classify

concepts can lead to decreased performance, especially in contexts where contexts and voice play an important role in emotional decision making.

In performance, when using NLTK + TextBlob to analyze the meaning of the content, the accuracy is 73.986365 and the F1 score is 66.012294. These measures involve a balance between simplicity and accuracy inherent in the NLTK + TextBlob approach. While it is suitable for tasks that require rapid observation and emotional evaluation, it may be disadvantageous in areas where clarity and detailed understanding of information is required. But NLTK + TextBlob is still an important tool in the NLP toolset and provides a lightweight and easy-to-use tool for sentiment analysis and word processing.

2.2 Textual Analyzer using VADER Algorithm

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a dictionary and rule-based assessment tool specifically designed to analyze emotions expressed in text. VADER, developed by researchers at the Georgia Institute of Technology, is particularly suitable for analyzing sentiment in newspapers, online comments, and other informal communication rules [26].

One of the main features of VADER is its dictionary, which contains a carefully selected list of words and their high scores. Each word in the dictionary is given a polarity score, indicating how well or poorly related the word is. In addition, the dictionary contains rules and instructions for dealing with emotions, negations, spelling, punctuation, and expressions that are often found in incorrect texts.

VADER uses logic-based logic that communicates the polarity score with the code to process the description to create the overall score of the script section. The emotional score ranges from -1 (very bad) to +1 (very good), with 0 meaning neutral. This measure allows VADER to capture nuances in thinking and interpret clear and ambiguous statements in text [24, 25].

Another important feature of VADER is its ability to manage expressions and slang popular in social media and online communication. By combining multiple languages and contexts, VADER is able to interpret emotions in false text, making it an important tool for analyzing emotions in various domains.

There are several steps aimed at analyzing the sentiment of the text using VADER (Valence Aware Dictionary and sEntiment Reasoner) [28].

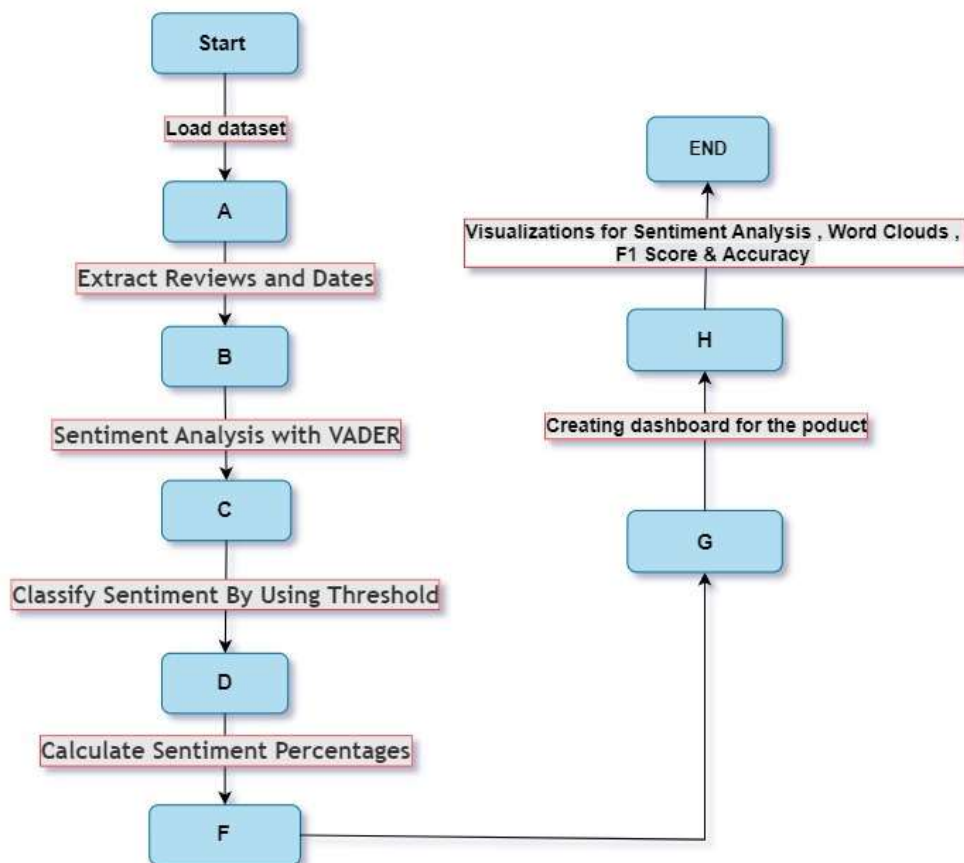


Figure 5. Flowchart of Code Implementation of VADER Algorithm

- **Data Preprocessing and Loading:** The sentiment analysis process begins with loading data containing analysis objects stored in JSON format. All individual reviews are extracted and placed in separate files by item.
- **Sentiment analysis using VADER:** After pre-processing and loading the data, sentiment analysis is performed on the comments. This code uses the VADER logic analysis tool, a key component of the Natural Language Toolkit (NLTK). Using VADER, the framework extracts a numerical representation of emotions from the content of the analysis.
- **Classification of opinions using threshold:** The polarity score obtained by VADER is used as the basis for classifying the opinions of each analysis. This classification system converts numerical scores into easily interpretable categories: good, bad, or neutral. This classification is made by reaching positive and negative results. Analyzes with polarity scores above a threshold were classified as positive. Conversely, reviews below a set threshold are classified as negative and trigger customer complaints. Reviews that fall within the specified range around zero are classified as average and indicate neither positive nor negative feedback.
- **Calculate the percentage of opinions:** Calculate the percentage of opinions for each category (positive, negative and neutral). This calculation provides a high-level view of the overall distribution across each product review. This calculation uses the sentiment classification (positive, negative, or neutral) assigned to each analysis in the previous step. This calculation results in the percentage of positive, negative, and average reviews for each product.
- **Visualization of Sentiment Analysis:** See percentage sentiment using the bar chart to get a deeper understanding. These recommendations provide a clear and transparent view of the customer's positive opinion of each product. Each bar in the visualization shows the percentage of positive, negative, and average reviews for a particular product over the years. This visual representation helps provide a clear understanding of how the customer's perception of the product changes over time. By analyzing trends in this view, product managers can identify moments of customer satisfaction or

dissatisfaction and use the context of the analysis to gain deeper insight into the root cause. Product Sentiment Dashboard: The final step involves integrating sentiment into the results analysis (visualizations, word clouds, etc.) into the product's dashboard. This dashboard acts as a central dashboard for product managers, providing a holistic view of customer needs. Control panels can contain a variety of content, including:

1. The chart shows the distribution of sentiment (positive, negative, neutral) over time.
2. The word cloud found the most frequently used words in positive, negative and neutral reviews.
3. The table includes important metrics like average review score and percentage of recommendations.

Despite some minor shortcomings, such as limited accuracy in detecting abnormal behavior, VADER has shown great potential in detecting emotions, especially in identifying positive and neutral emotions. With an accuracy of 67.34521 and an F1 score of 54.46231, VADER provides satisfactory analysis capabilities for a variety of applications.

Although VADER has many advantages such as being simple, fast and effective in detecting positive and neutral, it may show limitations in detecting negative, especially in cases where there are subtle or subtle changes [27 , 32]. Additionally, VADER's performance may vary depending on the quality and service of its dictionary and may require occasional updates and adjustments to suit particular features or texts.

Overall, VADER represents a powerful and useful tool for affective research projects, especially in cases of unofficial documentation where the traditional machine learning process would run into problems. It makes it easy and efficient for researchers, businesses, and professionals to seek insights from the literature by providing an explanation based on the necessity of scoring and evaluation according to the law.

2.3 Textual Analyzer using Word2Vec Algorithm

Word2Vec, a pioneering algorithm in the field of natural language processing (NLP), has played an important role in improving our understanding of text. Unlike traditional models that process text sequentially, Word2Vec introduces diversity by learning to classify the representation of a word in a continuous space. Its importance lies in its ability to capture the semantic relationship between words, revolutionizing the method of machine translation.

Word2Vec uses a neural network architecture to create word embeddings, which are essentially dense vector representations of a word. By analyzing the context in which words appear in the body, Word2Vec learns to represent words with similar meanings as closely related vectors in vector space. This enables Word2Vec to capture the ambiguous meaning and relationship of a word, allowing it to understand words contextually [29].

One of the unique features of Word2Vec is its ability to learn from large texts in an unsupervised manner. Through techniques such as Cross-Gram and Continuous Bag of Words (CBOW), Word2Vec can train large datasets to produce good words. Embeddings encode semantic meaning and syntactic structure, allowing Word2Vec to understand the message correctly.

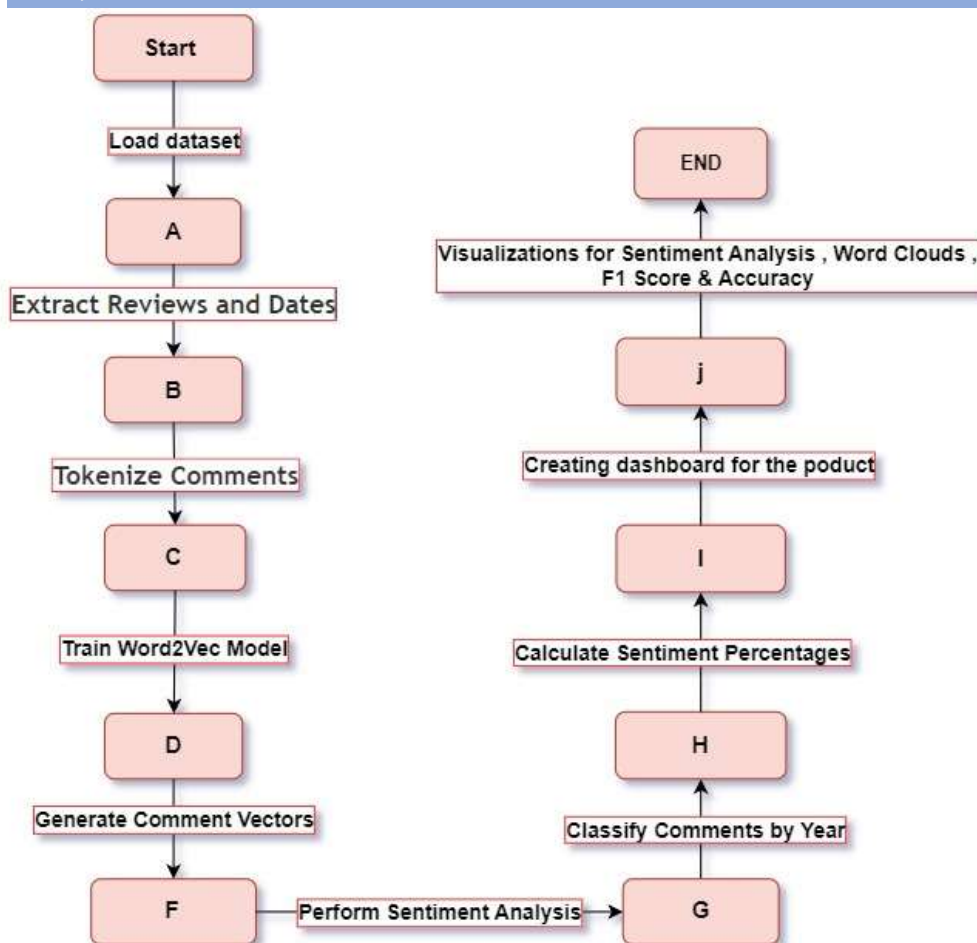


Figure 6. Flowchart of Code Implementation of Word2Vec Algorithm

- **Data Loading and Preprocessing:** The bootstrapping program checks the dataset in JSON format. Each review and its corresponding date are extracted and organized into a structure like a DataFrame. Use pre-written processes to cleanse your data, including removing pauses, tags, and tokenization. Tokenization involves splitting text into individual words or tokens and is a necessary step for the Word2Vec model to process data.
- **Meet the Word2Vec model:** The Word2Vec model is a neural network-based method that learns to represent words as continuous vectors in high-dimensional space. Word embeddings capture the semantic relationship between words based on their relationship in the whole. The Word2Vec model is first trained on the data, allowing it to learn individual word representations and relationships in the data.
- **Sentiment Analysis:** Once a Word2Vec model is trained, it can be used for sentiment analysis. - Examine the text. For each comment or review, calculate the average vector of its entries. The mean vector serves as a representation of the semantic content and overall meaning of the analysis. The analysis hypothesis is then determined based on the properties of the mean vector. The process of hypothesis analysis may include tools such as comparing mean vectors to predefined hypotheses or using machine learning classes learned in the recorded language. Using word embeddings and semantic relationships captured by the Word2Vec model, views of each test can be analyzed effectively and separately.
- **Visualization:** Various visualizations are used to better understand and interpret the results of meditation. Graphs can be used to show the perspective of time, showing the distribution of positive, negative and average values over different time periods (e.g. years). Additionally, word clouds can be created to visualize relevant emotional content and gain insight into the key concepts and concepts associated with different groups of emotions.

- **Accuracy Evaluation:** Evaluation of the effectiveness of the hypothesis testing model is based on Word2Vec embeddings and can calculate accuracy indicators such as accuracy and F1 score. This involves comparing model predictions with ground truth maps or theoretical records. By measuring accuracy and F1 scores, the strengths and weaknesses of the model can be identified and areas for potential improvement can be identified.
- **Create a control panel:** At the end of the analysis, it will create a control panel or interactive interface. An interface for visualizing analytical results and visualizations. The dashboard acts as a central hub for users to explore and interact with their data, allowing them to identify needs, view cloud messages, and gain insights into paper documents. By following this approach, the Word2Vec algorithm can be effectively used for sentiment analysis, preserving relationships in data, and performing sentiment classification. Data preprocessing, model training, sentiment analysis, visualization, accuracy assessment, and dashboard design are combined to provide effective solutions for analysis and insight in the whitepaper.

In general, the use of Word2Vec sentiment analysis includes preliminary data, model training, sentiment classification, visualization and evaluation process. By following these steps, analysts can understand the perspective of the data and make informed decisions based on expected results.

However, despite its powerful capabilities, Word2Vec has its limitations. The main problem is that it cannot capture the entire meaning of the sentence or word in a single document. Because Word2Vec processes each occurrence of a word independently, it may have trouble processing polysemy, or words that have more than one meaning. Additionally, Word2Vec may face challenges from rare words or poorly represented words in the training data [29, 30].

Another limitation of Word2Vec is the size representation of a single word; This may not be enough to capture the difference in meaning and nuance within a language. This can lead to decreased performance on tasks that require in-depth understanding of text, such as emotional analysis or language comprehension.

Despite these limitations, Word2Vec is still an important technique in NLP and forms the basis of many methods such as LSTM, BiLSTM and BERT. By addressing its shortcomings and leveraging its strengths, researchers can continue to leverage the power of Word2Vec for a variety of applications in language understanding and text analysis.

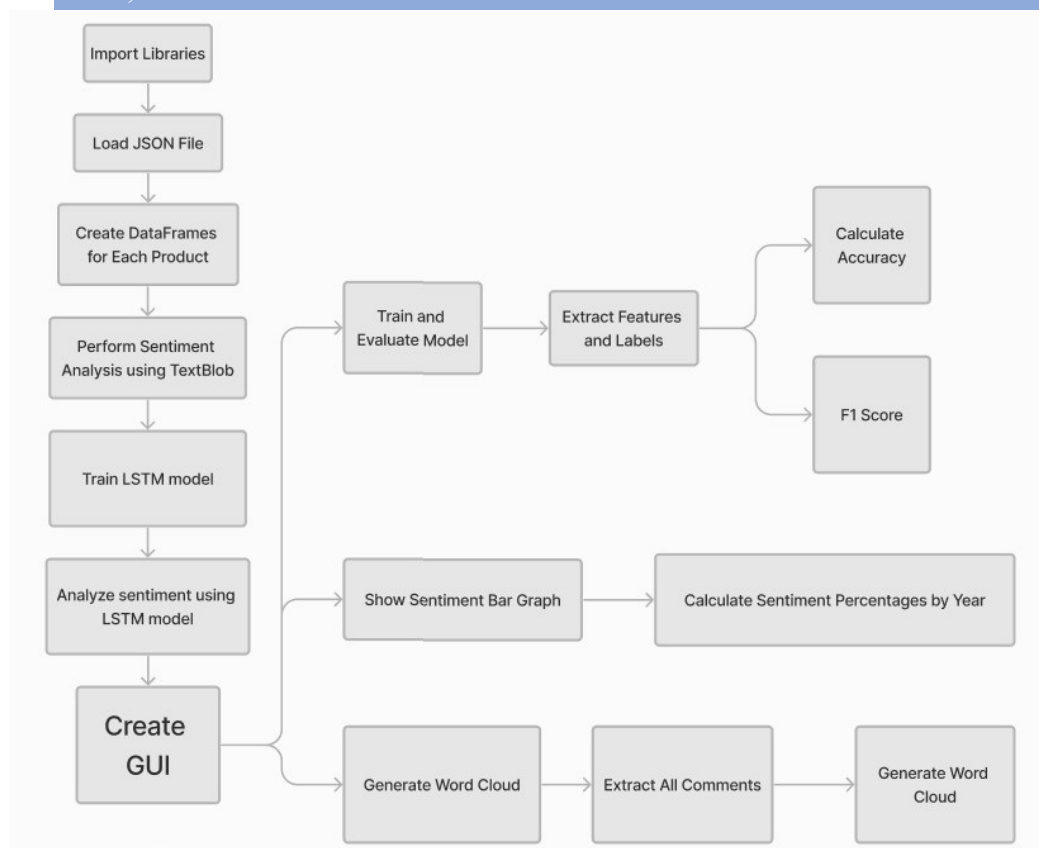


Figure 7. Flowchart of Code Implementation of LSTM Algorithm

- **Data Loading and Preprocessing:** The process begins with importing the library required for data processing and analysis. Upload a JSON file containing Amazon product reviews and organize the data into separate DataFrames, with each DataFrame representing a review for a specific product. This step ensures that the data is organized and ready for further analysis.
- **Sentiment Analysis Function:** This code contains two main analysis functions: one uses TextBlob, the other uses LSTM models:
 1. **TextBlob Sentiment Analysis:** This function uses the TextBlob library to analyze advertising messages. The score for the gender gives it an emotion (good, bad, or neutral).
 2. **LSTM Sentiment Analysis:** This project introduces and uses the LSTM (Long Short-Term Memory) model for sentiment analysis. The LSTM model architecture consists of the following layers:
 1. **Embedding layer:** Converts tokenized text strings into dense vector images.
 2. **Spatial Release layer:** Request release regularly to avoid overload.
 3. **LSTM layer:** The main feature that processes data sequentially and eliminates long-term dependencies.
 4. **Layer thickness:** Map the output of the LSTM layer to the desired label.

LSTM function collects text data, data link to ensure its length, converts thought symbols into gold coding, and divides data into educational and training materials. Experimental setup for model training and evaluation [35].
- **GUI creation:** The code uses the Tkinter library to create a graphical user interface (GUI). This GUI allows users to interact with emotional analysis functions in a user-friendly environment. It includes a menu for selecting item names, sentiment analysis buttons, and a framework for displaying views and results created during analysis.
- **Model Learning and Evaluation:** This code introduces and evaluates the LSTM model for statistical analysis. It extracts features (tokenized text strings) and labels (emotional levels) from the analysis. The LSTM model is trained

using training data and its performance is evaluated against test data. Additionally, the code tests the trained LSTM model against previous analysis to demonstrate its predictive ability and evaluate its accuracy on the distribution hypothesis.

- **Validity analysis and F1 score:** Numerical accuracy and F1 score are calculated to evaluate the performance of the hypothesis testing model. While the accuracy metric measures the proportion of correct distributions, the F1 score provides an equal measure of accuracy and recall, including both false positives and false negatives [Data is incorrect].
- **Visualization in Dashboard:** Rules provide more power to visualize the perspective of the analysis:
 1. **Sentiment Bar Chart:** This function creates a bar chart showing the positive, negative distribution of the selected product over several years. and unbiased thoughts.
 2. **Word Cloud:** This code includes the functionality to create a visual word cloud that shows the most frequently occurring words in the document. This can provide insight into the key concepts and topics discussed in product reviews.
 3. **Network Diagram (not shown in the flowchart):** The code also includes functionality to create a diagram that represents the relationship between messages by date. This visualization can help identify patterns and connections in materials.

By following this approach, the LSTM algorithm can effectively use the concept of product analysis. The combination of data loading and prioritization, predictive analytics (TextBlob and LSTM), GUI design, visualization, model training and evaluation, and fact/F1 data scorecard provides a powerful and comprehensive solution for analyzing and understanding sentiment. Paper documents. Overall, the code provides conceptual solutions, including preliminary data, model training, visualization, and user interaction. However, the best performance of the LSTM model indicates the potential for improvement, indicating the need for further optimization or alternative methods in the analysis of emotions. Although LSTM models are known for their ability to capture and preserve the natural environment. Although there is information about continuity, the application presented in this case does not adequately demonstrate this potential. The inability of this model to identify hypotheses due to stringent training requirements and vulnerability highlights the challenges of using LSTMs for hypothesis analysis. Therefore, although LSTM is still a promising method for processing sequential data, its application in the context of emotional analysis needs further improvement and optimization to reveal its full potential and achieve better results [36].

2.5 Text Analysis Using the BiLSTM + TextBlob Algorithm

The Bidirectional Long Term Memory (BiLSTM) algorithm represents a major advance in text analysis and provides similar accuracy and performance. Unlike its predecessors, BiLSTM has the unique ability to extract the content of the text [38]. By connecting bi-directional functions, BiLSTM models can simultaneously analyze the past and future of the system, allowing them to understand progress remotely.

BiLSTM's framework adopts a competitive LSTM architecture that improves the understanding of the underlying message [40]. The difference between these sequential models allows BiLSTM to overcome the limitations of the decision process, capturing complex nuances and relationships in the data [39].

The unique feature of BiLSTM is its pre-training target which makes it efficient with data points. Through tasks such as Masked Language Modeling (MLM) and Next Sentence Prediction (NSP), BiLSTM learns to generate content embeddings that encode semantic and syntactic patterns [37]. This pre-training on large datasets enables BiLSTM to understand human-like language.

The code generally shows how to measure sentiment using the BiLSTM + TextBlob algorithm. It includes data loading, model training, sentiment analysis, and graphical user interface (GUI) development to facilitate interactive learning. The analysis dives into the main points of the application and highlights its effectiveness and potential for improvement.

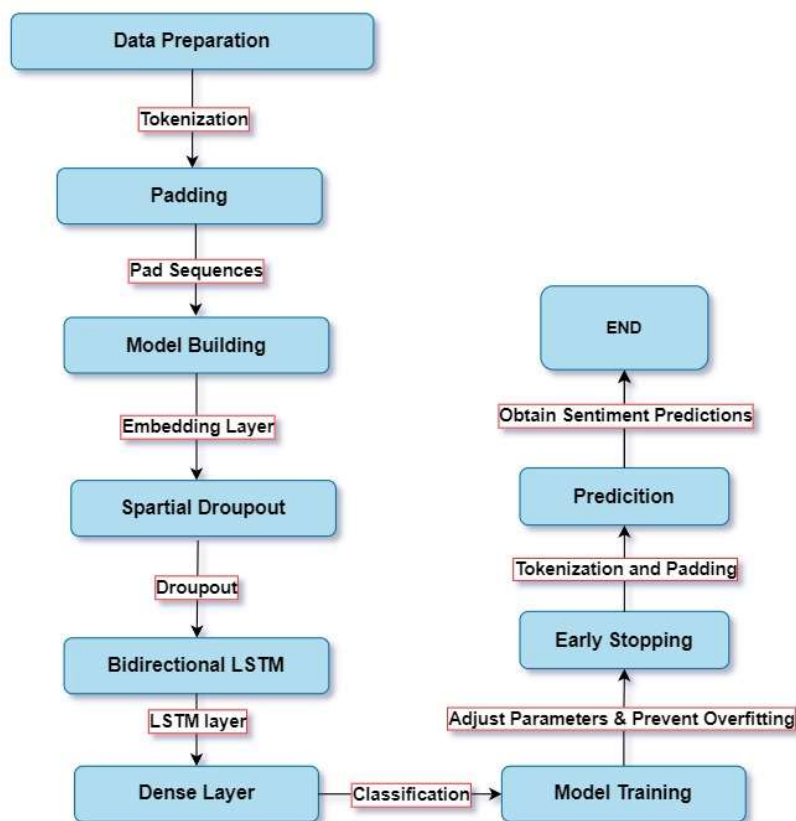


Figure 8. Flowchart of Code Implementation of BiLSTM + TextBlob Algorithm

- **Data Preparation:** The first step in the process is data preparation, which involves loading data (analysis elements) from the JSON file and setting it to a DataFrame model. This appropriate data is then subjected to symbolization, where the text is broken down into words or symbols. Padding is then used to ensure that the entire sequence is long; This is necessary so that the model can enter the material correctly.
- **Model Architecture:** The BiLSTM + TextBlob model is built using the TensorFlow Keras API, which provides high-level communication for deep learning modelling. The architectural model has the following layers:
 1. **Embedding Layer:** This layer converts the tokenized input sequences into dense vector representations, allowing the model to process the textual data effectively.
 2. **Spatial Dropout:** A dropout layer is applied to regularize the model and prevent overfitting.
 3. **BiLSTM + TextBlob Layer:** The core component of the model is the Bidirectional LSTM layer, which processes the input sequences in both forward and backward directions. This allows the model to capture context and dependencies from both directions, enhancing its ability to understand and interpret the textual data.
 4. **Dense Layer:** The final dense layer performs the classification task, mapping the output of the BiLSTM + TextBlob layer to the desired sentiment labels (e.g., positive, negative, neutral).
- **Model Training:** The data is divided into training and testing sets. The model is trained using TensorFlow Keras' fitting method, which optimizes model parameters based on data. To prevent overfitting, an early stop recall mechanism is used, which monitors the model performance of the validation process and stops training when there is no further improvement.
- **Sentiment Prediction:** After the training is completed, the BiLSTM + TextBlob model can be used for sentiment analysis. A special role was created to collect and record new feedback, send it to the training model and receive feedback. This feature allows users to use the trained BiLSTM + TextBlob model to determine the intent of text input.

- **Evaluation and Testing:** A series of preliminary analyzes with different hypotheses were tested to evaluate the effectiveness of the model. Each input is analyzed by learning the BiLSTM + TetBlob model and the predicted values are published. This step will help evaluate the accuracy of the model and identify potential problems or areas for improvement.
- **Graphical User Interface (GUI):** A Tkinter-based GUI was developed to provide an interactive platform for emotional analysis. Using options, users can select specific years for sentiment analysis, view charts, create word clouds, and view charts. Buttons are integrated into the GUI interface to be interactive, allowing users to interact with the system and perform various tasks related to intuitive thinking.

Based on this approach, the BiLSTM + TextBlob algorithm is effectively used for sentiment analysis by leveraging the power of deep learning and natural language processing. The combination of data preparation, modelling, training, prediction and evaluation, and interactive GUI provides a solution for analyzing and understanding sentiment from textual data.

Despite its high performance, BiLSTM + TextBlob may face problems in optimization and modification due to its resource-intensive nature and complex architecture [38]. Additionally, the nature of the black box can inhibit interpretation and create challenges in areas where transparency is important. Additionally, the performance of BiLSTM + TextBlob may vary depending on the quality and diversity of training data and may lead to errors in some cases.

But BiLSTM + TextBlob is still a powerful tool in natural language processing and provides excellent performance on many language understandings. Based on computational methods, data quality and predefined model, researchers can unlock the full potential of BiLSTM + TextBlob and use its capabilities for a variety of applications.

2.6. Textual Analyzer using BERT Algorithm

BERT, or Transformers' bidirectional encoder represents a revolution in natural language processing (NLP), revolutionizing the way machines interpret and understand written data. Its importance lies in its extraordinary ability to understand words in context, capturing complex nuances and dependencies in the text. The core of BERT adopts the Transformer architecture, which is different from sequential models such as neural network (RNN) and convolutional neural network (CNN) [41]. Transformer uses a self-tracking algorithm that causes each word or token in a sequence to simultaneously focus on other words or tokens, regardless of their position. This bidirectional tracking mechanism allows Transformers to capture long-term expectations in the text and overcome the limitations of sequential models that process ideas in a fixed order.

BERT is unique in its pre-training target supporting its embeddings and context data. BERT is pre-trained using two main algorithms: Masked Language Modeling (MLM) and Next Sentences (NSP) [41]. In MLM, some of the input tokens are randomly masked, making it difficult for the model to predict the masked tokens based on the surrounding context. This encourages BERT to learn a single representation of a word, allowing it to capture previous and subsequent context. NSP, on the other hand, involves predicting whether two sentences appear connected in the text, thus facilitating the understanding of sentence relationships and relations [43].

By pre-training on large datasets, BERT gains the ability to create content embeddings that encode semantic and syntactic patterns. These installations show the relationship between a word and its surrounding context, allowing BERT to understand words like a human. Therefore, when optimized for specific tasks such as sentiment analysis, BERT outperforms traditional models due to its in-depth understanding.

The implementation of sentiment analysis using BERT involves several key steps, each contributing to the overall functionality of the system.

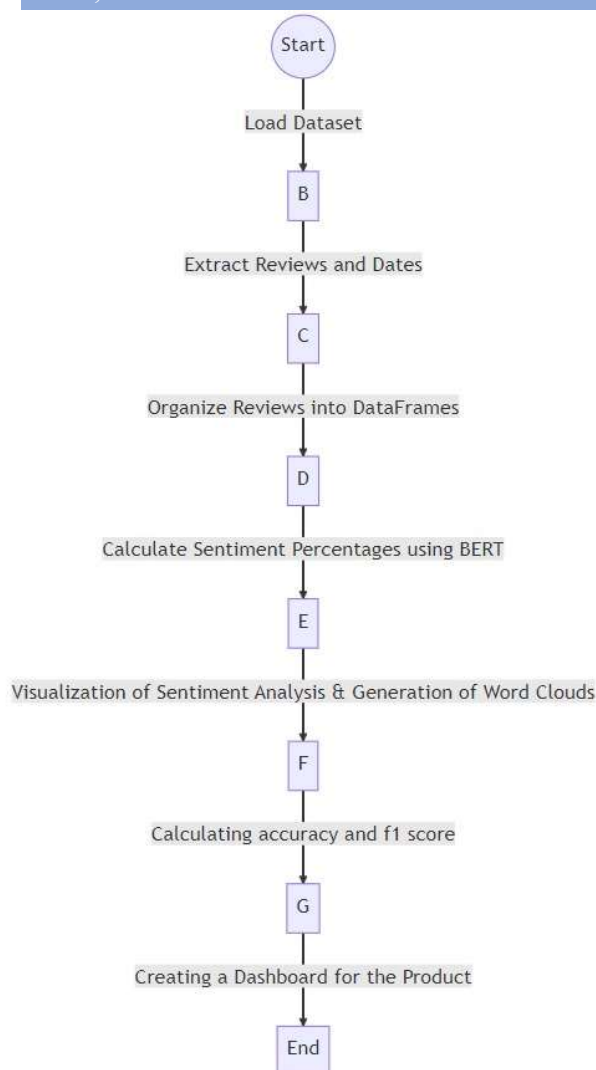


Figure 9. Flowchart of Code Implementation of BERT Algorithm

- **Data Preprocessing and Loading:** The program first loads a data file containing the analysis object stored in JSON format. Reviews are then extracted from the dataset and placed in individual DataFrames. Each DataFrame represents a review of a specific item. All reviews include a summary of the text and history [42].
- **Sentiment Analysis with BERT:** An important part of the application is relevance analysis using BERT (Bidirectional Encoder Represented with Transformers), situation analysis - the language model of the situation created by Google. This analysis uses BERT templates from the “transformers” library, specifically the “BertTokenizer” and “BertForSequenceClassification” groups. The emotional assessment process includes the following steps:
 1. **Tokenization:** Use “BertTokenizer” to tokenize the content of each message. This step converts the text into tokens at a level that the BERT model can process.
 2. **Model Inference:** The tokenized text is passed through the “BertForSequenceClassification” model, which produces logits (log-dds) for each desired value (positive, negative or neutral).
 3. **Sentiment Prediction:** The sentiment label with the highest score among the generated logits is assigned as the predicted sentiment for the corresponding review.
- **Calculation of Sentiment Percentages:** After determining the sentiment of each review, the next step is to calculate the sentiment percentages for each category (positive, negative, neutral). This is achieved by iterating through

the reviews and counting the occurrences of each sentiment label. The total number of reviews is used to calculate the percentage of each sentiment category, providing an overview of the sentiment distribution across the dataset.

- **Visualization of Sentiment Analysis** Sensitivity percentages are visualized using graphs to better understand and interpret sentiment results. Each bar represents the percentage of positive, negative, and average reviews for a product or company. These agreements ensure that common sentiments about each product are accurately represented, making it easier to compare and identify patterns.
- **Generation of Word Clouds:** In addition to sentiment analysis, character clouds are also included. A word cloud graphically represents the most frequently used words in the analysis. By visualizing key concepts in a word cloud, users can understand all the thoughts, discussion points, and recurring themes in the collected data.
- **Accuracy Assessment:** To evaluate the performance of the sentiment analysis model, the accuracy metric can be calculated. This involves comparing the predicted sentiment labels with the ground truth labels, where available. The accuracy metric measures the proportion of correctly classified instances, providing an indication of the model's performance in accurately classifying the sentiments of the reviews. Additionally, the F1 score can also be computed to provide a balanced measure of precision and recall, taking into account both false positives and false negatives.

Creating a Dashboard: The final step in the process is the creation of a dashboard or interactive interface to present the sentiment analysis results and visualizations. This dashboard serves as a centralized platform for users to explore and interact with the data, allowing them to analyze sentiment trends across different products, view word clouds, and gain valuable insights from the textual data.

By following this approach, the BERT algorithm is effectively used to analyze objects. Preliminary data, sentiment analysis using BERT, percentage viewpoint calculation, visualization (line charts and word clouds), accuracy assessment and design dashboard are combined to provide analysis and insight solutions for project data. (Bidirectional encoder represented by Transformers) is a powerful tool for understanding natural language, including logic analysis, but the absolute truth of 68.57189 can be seen. Some reasons for this disadvantage may be:

- **Data Requirements:** BERT's performance heavily depends on the quality and quantity of the training data. To achieve optimal results, fine-tuning BERT necessitates large-scale labeled datasets, which may not always be readily available or feasible to acquire.
- **Lack of Interpretability:** BERT operates as a black-box model, making it challenging to interpret its decisions and understand how it arrives at particular predictions. This lack of interpretability can be a significant limitation in applications where transparency and explainability are crucial.
- **Resource Intensiveness:** Fine-tuning BERT requires substantial computational resources and time. The model's large size and complexity demand powerful hardware for training, making it inaccessible for researchers or organizations with limited computing capabilities.
- **Overfitting:** Fine-tuning BERT on small or unrepresentative datasets can lead to overfitting, where the model performs well on the training data but fails to generalize to unseen examples. Overfitting diminishes the model's ability to make accurate predictions on real-world data.

2.7 Textual Analysis using BERT + TextBlob Algorithm

The integration of BERT (bidirectional encoder represented by Transform-ers) with rule-based analysis in the TextBlob library represents an attempt to simplify and interpret TextBlob in order to improve the correction theory of the BERT model. This combination combines the advanced understanding of content provided by BERT with the rule-based analysis capabilities of TextBlob to provide better understanding of the information to be read. The BERT + TextBlob algorithm creates content embeddings by first processing the text in the BERT model, which are then added with polarity scores obtained from TextBlobs. By combining these two sources of information, the algorithm tries to place more informed and detailed information about the user's needs in the database.

However, despite its novelty and early promise, the BERT + Text-Blob algorithm exhibits some important features. Disadvantages that affect its effectiveness in emotional evaluation. The complexity and resource efficiency of the BERT model is a significant limitation. BERT, a deep learning model with many parameters, requires significant computing resources for training and reasoning; This makes distribution and competition difficult, especially in limited areas. Additionally, relying on pre-learning BERT embeddings may limit the algorithm's ability to adapt to certain nuances and changes in language usage, resulting in poor performance on some details.

Moreover, while TextBlob integration adds translation and convenience to the process, it also brings with it some disadvantages that may affect its overall performance. TextBlob's rule-based sentiment analysis lacks the intelligence and context knowledge of higher-level machine learning models; This leads to incorrect assumptions, especially in nature clusters that contain difficult or ambiguous words. Additionally, reliance on pre-existing rules and regulations may limit TextBlob's ability to capture sentimental changes in leading and content-driven culture behaviors, which may further impact reliability and generality.

To know the process of the programming process, it is necessary to investigate its basic features, especially the review opinion in the product review. The purpose of this application is to first process the data and make hypotheses using the complex BERT algorithm and TextBlob and see the results. Let's go through each step-in detail to show how the code processes data and provides useful information from it.

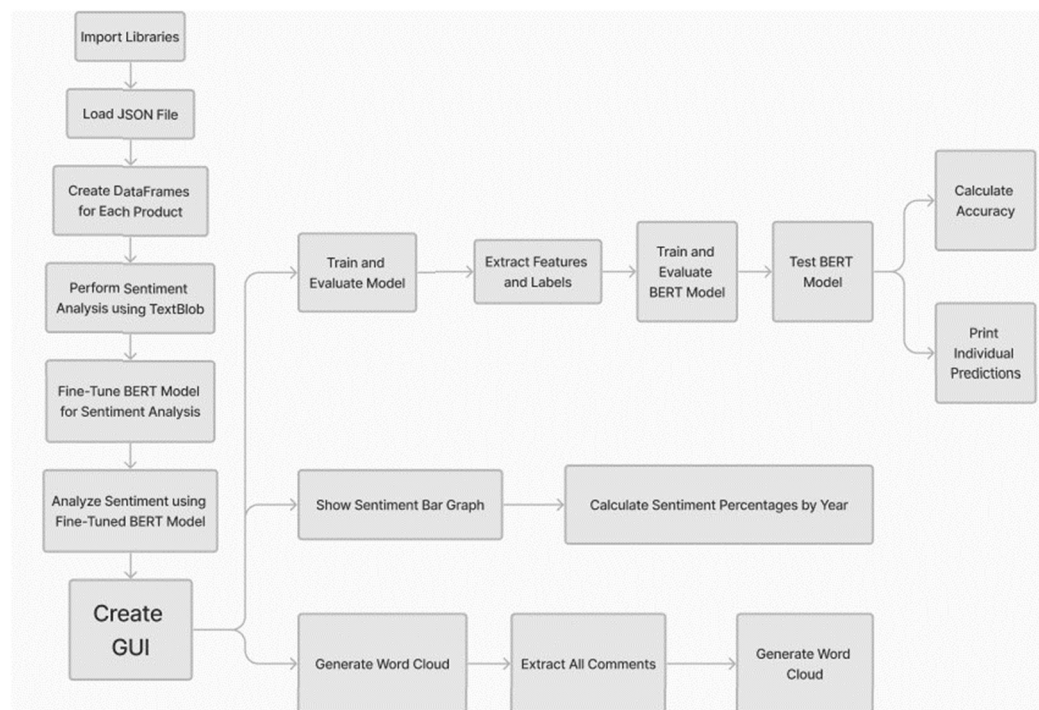


Figure 10. Flowchart of Code Implementation of BiLSTM + TextBlob Algorithm

- **Data Preparation and Loading:** The process begins by importing the required library and loading the JSON file containing product review information. This information is created in separate files for each item, allowing analysis and organization.
- **Sentiment Analysis:** The concept analysis phase consists of several steps. The TextBlob library is used to perform sentiment analysis in text analytics and provides a simple and effective way to determine sentiment polarity (positive, negative, or neutral) based on its work. At the same time, the BERT (Bidirectional Encoder Represented by Transformers) model is trained and tested for sensitivity testing. This deep learning model uses the BertTokenizer and BertForSequenceClassification classes from the Transformer library to perform meaningful content analysis of text for

classification purposes. Extract important features and similar sentiment labels from data analysis to facilitate model training and evaluation. The trained BERT model is tested on a separate test set to evaluate its performance in emotion classification. According to the evaluation results, the BERT model is well-tuned, and its analysis capabilities can be improved by correcting the negative and negative aspects of the model to better capture the nuances of opinion in the literature review. A fine-tuned BERT model is used to analyze sentiment analysis using the ability to understand context to provide better insights. The accuracy of TextBlob and BERT-based thinking in the analysis model is calculated by comparing its predictions with the real text (if available). This measurement helps evaluate the effectiveness of each method and recommend further improvements.

- **Dashboard Creation for Sentiment Analysis:** The dashboard is designed to provide users with information on analyzing sentiment of product reviews. It provides three main functions:

1. **Visual analysis:** Users can use graphs to visualize wiring. These charts show the percentage of good, bad, and average reviews for each product, allowing users to quickly understand their need to take care of different things.

2. **Word cloud creation:** The dashboard helps create a word cloud that shows the most common words in the word. These features help users understand all the ideas and content discussed by providing information about the key concepts and topics discussed in the message.

3. **Accuracy evaluation:** Users can evaluate the accuracy of sample requirements directly from the control panel. By training the model and calculating metrics such as accuracy and F1 score, users can evaluate the model's performance in opinion classification and provide useful feedback on confidence in survey results.

The above description, along with the content in the workbook, provides an overview of the conceptual analysis process, including data preparation, analysis of applied theory TextBlob and BERT, model training and optimization, accuracy testing, visualization, and user interface development. Despite these limitations, the BERT + TextBlob algorithm has great performance that is worth considering. A key advantage is the ability to leverage the power of BERT and TextBlob to combine meaningful content with simple rules for better analysis. Additionally, the design of the algorithm allows for changes and modifications, allowing developers to tune the model and adapt it to some specific uses and applications. In addition, the integration of TextBlob's sentiment scores with BERT embeddings provides additional information that can improve the system's ability to detect ambiguous thoughts and correct whole truth.

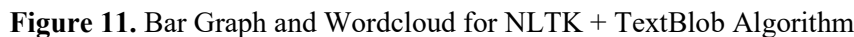
However, it is important to acknowledge the shortcomings and limitations associated with the BERT + TextBlob algorithm to ensure an accurate assessment of its performance and suitability for different applications. A major problem is that there may be a conflict between the complex representation learned by BERT and the simple reasoning model obtained by TextBlob, which can lead to inconsistency and inability to predict correctly. Additionally, relying on pre-learning BERT embeddings will prevent the algorithm from adapting to the specific data and context, so training data quality and domain importance should be carefully evaluated. In addition, the computational overhead and requirements of the BERT model can cause problems in real-world deployments, especially in environments with little money or little ability to succeed.

In summary, while the integration of BERT with TextBlob represents a new approach to sentiment analysis that combines deep learning with simple rules, its advantages, disadvantages and importance of work should be evaluated. By recognizing the limitations of algorithms and leveraging their performance, developers and experts can use the potential of the algorithm to improve thinking through analysis and ensure compatibility of results from data across different types of applications.

3. Results

In order to evaluate the effectiveness of various theories of analysis algorithms, we present visual results and insights obtained from the analysis of the analyzed products. Each algorithm is evaluated on its ability to correctly identify positive, negative, and neutral hypotheses. The following description summarizes the results from the export sensitivity analysis and the main points from the analysis.

3.1 NLTK + TextBlob



3.2 VADER



3.3 Word2Vec



Figure 13. Bar Graph and Wordcloud for Word2Vec Algorithm

While Word2Vec excels in segregating positive and negative comments, it struggles with detecting neutral sentiments. Nevertheless, it accurately separates positive comments, resulting in a high level of accuracy. The word cloud emphasizes terms such as "phone" and "camera."

3.4 LSTM

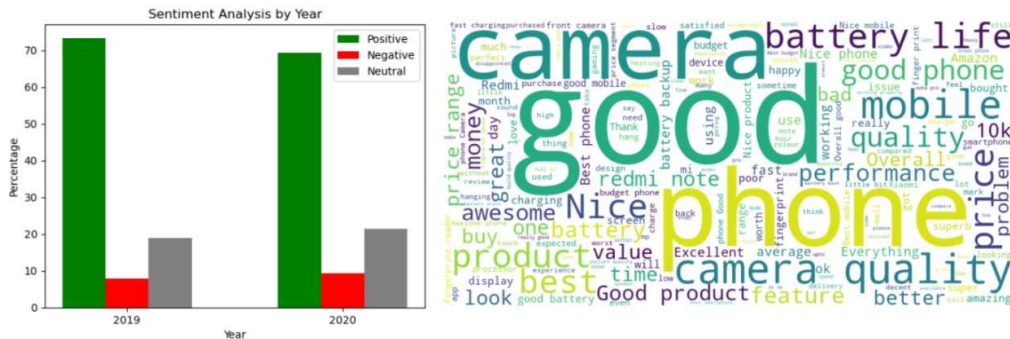


Figure 14. Bar Graph and Wordcloud for LSTM Algorithm

The bar plot for LSTM reveals an imbalance, with a high number of positive comments and a scarcity of neutral and negative comments. There is a clear misclassification trend, where negative comments are labeled as neutral, and neutral comments are classified as positive. The word cloud emphasizes terms like "phone," "camera," "quality," and "battery life."

3.5 BiLSTM + TextBlob

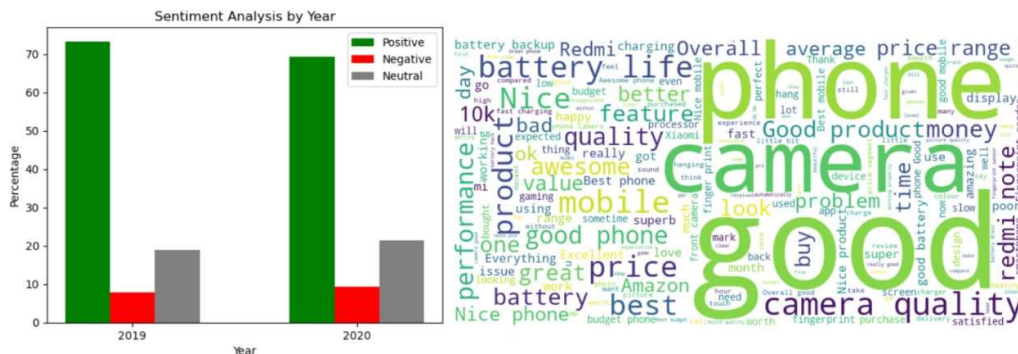


Figure 15. Bar Graph and Wordcloud for BiLSTM + TextBlob Algorithm

BiLSTM + TextBlob stands out as the most successful analyzer, accurately classifying comments into positive, negative, and neutral categories. This model achieves the highest accuracy and F1 score among the considered algorithms. The word cloud highlights various terms reflecting the diverse sentiment expressions.

3.6 BERT

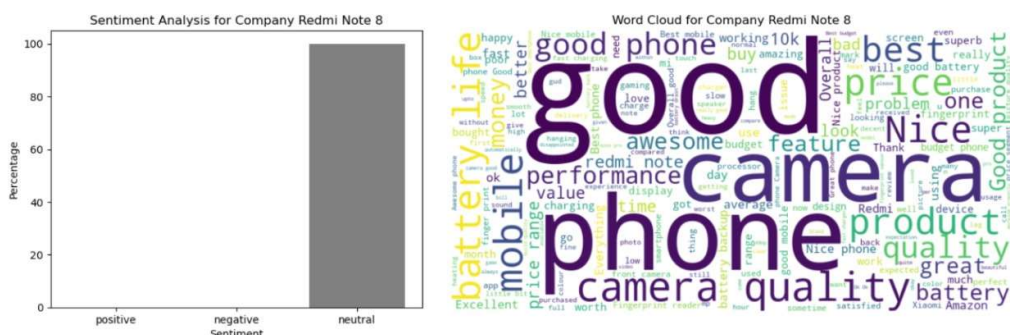


Figure 16. Bar Graph and Wordcloud for BERT Algorithm

3.7 BERT + TextBlob

**Table 1.** Collection of Accuracy and f1Score for all Algorithms

Analyzers	Accuracy	f1 Score
NLTK + TextBlob	73.98636	66.01229
VADER	67.34521	54.46231
Word2Vec	80.01435	79.56448
LSTM	69.94812	66.34523
BiLSTM + TextBlob	97.70124	86.21153
BERT	68.57189	73.93184
BERT + TextBlob	66.21457	68.63781

4. Conclusions

Our method will take you on a journey of several stages, starting with good data preparation and sentiment analysis using TextBlob and BERT. We then dive into the complex process of model training and refinement to ensure our algorithms capture the nuances of emotion. Accurate measurement is an important step that provides insight into our performance standards and guides us to continuous improvement.

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organization. These visualizations bring users' thoughts to life, allowing you to clearly see the importance of their experiences and opinions.

An important part of our job is the ability to analyze the emotions of the time. By calculating the percentage of reviews in a year, we enable businesses to predict changes in customer sentiments and opinions, improve their ideas and adapt to emerging issues. This agreement is important in today's business world, where customer loyalty is hard earned and easy to lose.

We also put together the word cloud to show a tool that goes beyond a pretty visual but is a window to loyal customers. The voice of your customers. By showing the most frequently used words in their analysis, we revealed different concepts, pain points and areas of interest, leading to the repair of zoning plans and construction materials.

But let's not forget the unsung hero of our sentiment analysis solutions: user-friendly graphical user interfaces (GUIs). This intuitive platform works as a command center, allowing you to seamlessly interact with our system, access data analysis, select analysis options, and easily visualize benefits. Emotions, word clouds and personal predictions appear together on your canvas, allowing you to make decisions with confidence.

Here's where the real magic happens: control panel integration. The dashboard is at the heart of our analytics solution, the main platform that collects and presents our insights in an open and collaborative way. By integrating multiple views, dashboards enable stakeholders to understand the entire perspective of the picture at a glance, thus encouraging collaboration and communication among the team.

Imagine a world where product development, marketing and customer teams are united through the integration of customer insights, where insights flow seamlessly, and decisions are made with a deep understanding of the voice of the customer. This is the power of our emotional analytics solution, expanded by the central role of dashboards.

Finally, our approach is more than a set of algorithms and analyses; It's a testament to the importance of data-driven analytics and listening to the voice that matters most: your customers. By using our emotional intelligence, we not only increase competition; You are on a journey of continuous improvement where customer satisfaction is the guide and innovation is the last resort.

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