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Sentimental Analysis for Product Reviews Using NLP

By
[1]NAVIN R. (713321CS030)
[2]NIVESH SB (713321CS031)
[3]VIGNESHWARAN M. (713321CS057)

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BONAFIDE CERTIFICATE

Certified that this Project Report titled, "**SENTIMENTAL ANALYSIS FOR PRODUCT REVIEWS USING NLP**" is the bonafide record of "**NAVIN R, NIVESH SB, VIGNESHWARAN M"** who carried out the Project Work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE	**SIGNATURE**
Dr. K. PERIYAKARUPPAN	Ms. P. DEEPA
HEAD OF THE DEPARTMENT	**SUPERVISOR**
Professor and Head, Department of Computer Science & Engineering, SNS College of Engineering, Coimbatore-641 107	Assistant Professor, Department of Computer Science & Engineering, SNS College of Engineering, Coimbatore-641 107

Submitted for the Project Viva-Voce examination held on ……………….

Internal Examiner **External Examiner**

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ABSTRACT

In today's online shopping world, product reviews significantly impact customer purchasing decisions, but the vast number of reviews makes it difficult for businesses to analyze them manually. This project uses Natural Language Processing (NLP) to automate sentiment analysis, allowing businesses to quickly understand customer opinions. By categorizing reviews as positive, negative, or neutral, the project provides valuable insights into customer sentiment. The process begins by gathering and cleaning a dataset of product reviews, followed by steps like removing unnecessary words, breaking down sentences, and simplifying words for more accurate analysis. With these preparations, machine learning models such as Naive Bayes and Support Vector Machines (SVM) predict sentiment trends in new reviews, which are then visualized in pie charts for clarity. This automation helps businesses grasp customer needs, leading to improvements in marketing, product development, and customer service. Ultimately, this system allows companies to turn vast amounts of feedback into actionable insights, making it easier to create customer-centered products and strategies.

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LIST OF ABBREVIATIONS

RNN	Recurrent Neural Network
AI	Artificial Intelligence
IOT	Internet of Things
SA	Sentiment Analysis
LSTM	Long short term memory
PCA	Principal Component Analysis
SQL	Structured Query Language
NLP	Natural Language Processing
CNN	Convolutional Neural Network
API	Application Programming Interface

CHAPTER ONE
INTRODUCTION

In today's digital era, e-commerce has revolutionized shopping by offering consumers access to a vast range of products online. A crucial part of this shopping experience is consumer feedback, often provided through online reviews. These reviews are typically the first piece of information that potential buyers encounter when exploring products, influencing their perceptions and purchasing decisions. However, with the sheer number of products available and the overwhelming volume of feedback, both consumers and businesses can struggle to make sense of it all. This project focuses on using sentiment analysis—a computational technique that categorizes and interprets sentiments expressed in text—to analyze product reviews, aiming to benefit both customers and businesses through actionable insights. In product reviews, sentiment analysis helps to identify whether feedback is positive, negative, or neutral. This classification of opinions is valuable to companies because it allows them to understand customer satisfaction, measure product performance, and address specific concerns or suggestions. For consumers, sentiment analysis provides clarity in decision-making by summarizing reviews into concise categories, enabling them to quickly assess a product's overall reception.

The primary goal of this project is to apply sentiment analysis to product reviews and generate clear, informative summaries of customer sentiment. Classifying reviews into positive, negative, or neutral categories allows businesses to gauge customer satisfaction and product performance, while also assisting customers in making informed purchasing decisions. This sentiment analysis process begins with data collection, where a dataset of product reviews is gathered from popular e-commerce platforms. Collecting reviews from various products and categories ensures that the analysis represents a diverse range of customer experiences. After gathering data, the next step is preprocessing, which prepares the text for accurate sentiment analysis. Preprocessing involves breaking down text into individual words (tokenization), removing common words that do not contribute to sentiment (stop-word removal), and simplifying words to their base form (stemming). These steps clean the data by removing noise, enhancing the reliability of the analysis.

After preprocessing, sentiment classification algorithms are applied to categorize each review's sentiment. This project explores both machine learning methods, such as Naive Bayes and Support Vector Machines (SVM), and advanced deep learning approaches, such as neural networks. Evaluating these models based on accuracy and generalization helps determine the best approach for this project. Testing multiple models ensures that the chosen technique not only performs well but also adapts effectively to different types of reviews. Visualizing the distribution of sentiments for different products provides valuable insights for both businesses and consumers. For companies, these visual summaries enable quick assessments of customer feedback, while consumers benefit from an easy-to-understand overview of product sentiment. Additionally, interactive elements could allow users to filter results by specific criteria, such as product category or time period, providing a more personalized analysis experience.

The impact of sentiment analysis in e-commerce extends beyond simply evaluating products. By understanding customer sentiment, businesses can make improvements to products, foster customer loyalty, and enhance marketing strategies. Addressing negative feedback allows companies to improve their offerings and demonstrate to customers that their opinions matter. This responsiveness can lead to increased customer trust and loyalty, which are essential in the competitive e-commerce landscape. For consumers, sentiment analysis simplifies the often-overwhelming task of reviewing multiple comments, enabling them to make confident, informed purchasing decisions. This clarity in understanding product sentiment enhances the shopping experience, making it more efficient and satisfying.

In conclusion, this project on sentiment analysis for product reviews aims to bridge the gap between consumer opinions and business strategies by utilizing computational techniques to classify and visualize sentiment. The insights gained from this analysis empower both businesses and consumers in a rapidly evolving digital marketplace. As e-commerce continues to grow, understanding customer sentiment will become increasingly important, helping create a more transparent and informed marketplace. By focusing on customer feedback, companies can enhance their products and foster stronger customer relationships, while consumers enjoy a simpler, more effective shopping experience. This project aspires to contribute to a smarter, more customer-centric approach to e-commerce, benefiting both businesses and customers in the long term.

CHAPTER TWO
LITERATURE REVIEW

"M. Sharma, "Sentiment Analysis of Amazon Reviews Using Natural Language Processing," *International Journal of Data Science*, vol. 12, no. 4, pp. 123-135, 2023.

A. Gupta & P. S. R. Kumar, "Leveraging TextBlob for Sentiment Analysis in E-Commerce," *Journal of E-Commerce and Digital Marketing*, vol. 15, no. 2, pp. 55-70, 2022"

Sentiment analysis, also referred to as opinion mining, has become a prominent field of study within natural language processing (NLP), especially due to the surge in user-generated content on the internet. Product reviews on e-commerce platforms are one of the primary areas where sentiment analysis is applied, as it helps consumers make purchasing decisions and enables companies to understand customer satisfaction. According to Liu (2012), sentiment analysis is crucial in the modern marketplace, providing valuable insights into consumer attitudes and helping businesses respond proactively to customer feedback. This growing demand for sentiment analysis in e-commerce has led to continuous research on improving the techniques used to classify and interpret opinions expressed in text data, particularly with machine learning and deep learning models. [1] [2]

"R. Patel, "An Overview of Sentiment Analysis and Its Application to Customer Reviews," *Journal of Business Intelligence*, vol. 10, no. 1, pp. 98-110, 2021"

Different methodologies have been applied in sentiment analysis, ranging from rule-based approaches to machine learning and advanced deep learning. Early studies by Pang and Lee (2008) introduced machine learning models, such as Naive Bayes and Support Vector Machines (SVM), which achieved notable accuracy in sentiment classification. These methods laid the foundation for sentiment analysis, and rule-based techniques using pre-defined sentiment lexicons, like the one developed by Hu and Liu (2004), were also effective but often lacked flexibility. Recent advancements include deep learning models, with Socher et al. (2013) introducing Recursive Neural Networks (RNNs) that could understand complex sentence structures, while Kim (2014) demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for text sentiment analysis. The introduction of Transformer-based models like BERT by Devlin et al. (2018) has further improved sentiment classification accuracy by capturing contextual nuances, allowing for more sophisticated sentiment analysis in product reviews. [3]

"K. L. Johnson, "Scraping and Analyzing Product Reviews: A Web-Based Approach," *Web Analytics and Applications Journal*, vol. 8, no. 3, pp. 210-225, 2020"

Sentiment analysis in e-commerce is particularly challenging due to the diverse language used in reviews and the range of product categories. Studies like those by Archak, Ghose, and Ipeirotis (2011) showed how sentiment analysis helps extract insights on specific product features, which aids companies in identifying customer preferences and potential improvements. Rui, Liu, and Whinston (2013) found that brands could monitor online sentiment trends to assess public perception, highlighting the role of sentiment analysis in reputation management. Supervised learning is the most common approach in these applications, where models are trained on labeled datasets to predict sentiment. However, as Feldman (2013) noted, obtaining labeled data for every product and category is costly and time-consuming, leading some researchers to explore unsupervised and semi-supervised models that require less labeled data, as seen in Poria et al. (2016). [4]

"A. Williams & H. Zhang, "Text Mining and Sentiment Analysis for E-Commerce Reviews," *International Journal of Data Analytics*, vol. 14, no. 5, pp. 145-160, 2022.

J. L. Morgan, "The Use of NLP for Customer Feedback Analysis in Retail," *Journal of Retail Technology*, vol. 9, no. 4, pp. 145-158, 2021"

Product reviews also present unique challenges, such as the presence of mixed sentiments, informal language, and sarcasm. Ganu, Elhadad, and Marian (2009) emphasized that these factors reduce the accuracy of traditional text processing methods, while Riloff et al. (2013) highlighted the importance of sarcasm detection, a task that remains difficult for even advanced models. Aspect-based sentiment analysis, as proposed by Pontiki et al. (2016), addresses mixed sentiments by evaluating opinions related to specific product features, offering a more granular view of customer feedback. The dynamic nature of consumer opinions also presents a challenge, as sentiments may shift due to seasonal trends or brand campaigns, requiring models to be adaptable over time. Agarwal et al. (2011) suggested that sentiment models need regular updates to remain relevant, particularly for high-turnover product categories. [5] [6]

“T. G. Smith, "Trends in E-Commerce Sentiment Analysis: An Overview of Tools and Techniques," *E-Commerce Data Science Review*, vol. 17, no. 2, pp. 79-92, 2023”

Visualizing sentiment analysis results is a critical step in making insights accessible to both businesses and consumers. Chamlertwat et al. (2012) noted the value of user-friendly visualizations, such as pie charts and bar graphs, which help non-technical users quickly understand sentiment trends. Interactive dashboards are becoming popular as they allow users to filter data by categories like time frame, sentiment type, and product, providing a more tailored analysis. These visualization tools are particularly helpful for businesses aiming to identify and address negative sentiment promptly, as seen in research by Kumar et al. (2016). Additionally, visualizations help consumers get an overview of product sentiment, assisting them in making faster and more informed purchase decisions. [7]

“B. M. Davis, "A Comparative Study of TextBlob and Vader for Sentiment Analysis," *Journal of Natural Language Processing*, vol. 20, no. 3, pp. 88-103, 202”

As the field of sentiment analysis evolves, ethical considerations around data privacy and responsible usage of customer data have gained attention. According to Crawford et al. (2014), privacy concerns are significant, especially as sentiment analysis relies heavily on user-generated data. With increasing awareness around data ethics, researchers are exploring techniques that ensure data security and protect user privacy. These ethical considerations are vital for maintaining public trust in sentiment analysis tools and encouraging consumers to participate in online feedback, thereby enabling a more transparent exchange between consumers and brands. [8]

“ P. Kumar & N. Singh, "Deep Learning Techniques in Sentiment Analysis for Product Reviews," *Advances in Artificial Intelligence and Machine Learning*, vol. 18, no. 1, pp. 36-49, 2021”

In conclusion, sentiment analysis has become a vital tool in the e-commerce industry, offering valuable insights from consumer reviews that benefit both companies and customers. The field has advanced from rule-based techniques to complex machine learning and deep learning models, which provide more accurate sentiment classification. However, challenges remain in analyzing mixed sentiments, handling informal language, and adapting to changing opinions. This project builds on these existing research foundations, utilizing both traditional NLP techniques and advanced GenAI methods to create a sentiment analysis system tailored for e-commerce product reviews, ultimately aiming to enhance the shopping experience and help brands respond to customer needs. [9]

CHAPTER THREE
DESIGN THINKING

A. Empathy

In a world where online shopping has become second nature, the value of honest and clear feedback can’t be overstated. Imagine you’ve just purchased a product online—maybe a new phone or a skincare product you’ve never tried. When you read through the reviews, you're hoping for insights from people like you who can give a genuine account of their experience. But with thousands of reviews, who has time to sift through them all? This is where your project steps in, making sense of all this information.

Sentimental Analysis for Product Reviews is like a friendly guide, sorting through mountains of opinions to help customers understand if a product is genuinely worth their time and money. By analyzing feedback in human terms positive, negative, or neutral it helps potential buyers make better, faster decisions. It’s not just data processing; it’s creating a bridge of trust between sellers and buyers, ensuring that people feel confident in their choices.

For businesses, it’s a way to listen and respond to customers' voices, understanding their strengths and areas for improvement in a way that feels personal, relevant, and genuinely insightful. Your project is not just about code and charts; it’s about building a better, more connected world of online shopping.

Think about how much better it feels when a product genuinely understands what you need or where you’re coming from. That’s what your project is doing showing businesses not just what people say, but how they feel about a product. Is it excitement, disappointment, relief? This sentiment analysis adds a human layer, helping companies connect to real emotions behind reviews.

With thousands of reviews, trying to choose a product can feel overwhelming, almost like reading through a never-ending novel. Your project steps in as a helpful friend, highlighting the main feelings from other customers so people can make quicker, more confident choices.

➢ *Survey*

- ***Rajesh-Local Arisanal Product Seller***

Rajesh believes that the analysis tool could help him understand customer sentiment toward his products. He thinks this would allow him to improve his offerings based on customer feedback trends and preferences.

- ***Anita-Small Business Owner, Home Decor Items***

Anita feels that knowing if customers generally like or dislike her products would help her tailor her designs. A sentiment analysis could be beneficial in predicting market success for new items.

- ***Ramesh – Handmade Jewelry Seller***

Ramesh struggles with mixed customer reviews and thinks that an analysis tool would help him identify specific areas for improvement, such as customer service or product quality.

- ***Priya – Independent Soap Maker***

Priya values customer feedback for product enhancement. She believes a platform that provides insights into positive and negative aspects of her products would help her refine her recipes to meet customer preferences.

- ***Vikram – Artisanal Chocolate Producer***

Vikram finds it hard to gauge how customers feel about his products. A tool that analyzes reviews would help him understand if customers enjoy the taste, packaging, or pricing.

- ***Geeta – Seller of Sustainable Fashion***

Geeta wants to know if her customers appreciate the eco-friendly aspects of her clothing. She thinks sentiment analysis could reveal whether sustainability impacts her customers’ purchasing decisions.

- ***Mohammed – Custom Furniture Maker***

Mohammed faces diverse feedback on his furniture designs. He believes an analysis tool could help him identify trends in reviews and allow him to better align with customer tastes.

- ***Lakshmi – Boutique Owner, Handmade Bags***

Lakshmi feels that knowing what customers like about her products would help her prioritize those features. She believes that an analysis tool could highlight qualities that lead to positive reviews.

- ***Sanjay – Handmade Pottery Seller***

Sanjay thinks that feedback analysis would help him focus on popular designs and understand any quality concerns customers might have. A platform that identifies sentiment could be highly beneficial.

- ***Neha – Organic Skincare Entrepreneur***

Neha believes that understanding customer satisfaction with her products' effectiveness and ingredients would help her better tailor her skincare line to customer needs.

- ***Rita – Eco-Conscious Consumer***

Rita wants to know if a brand she supports is genuinely committed to sustainability. A sentiment analysis tool could help her see if other customers appreciate the brand's eco-friendly efforts.

- ***Anil – Technology Product Reviewer***

Anil feels that a sentiment-based tool would allow him to see what other buyers think of tech products he's interested in, helping him make informed purchasing decisions.

- ***Karan – Frequent Online Shopper***

Karan likes knowing the overall feedback on items he's interested in. He thinks a sentiment analysis tool would help him quickly gauge how others feel about a product before buying.

- ***Sneha – Avid Book Reader***

Sneha often buys books based on reviews. She believes sentiment analysis would help her pick books by highlighting the main themes other readers enjoy or dislike.

- ***Amit – Sports Gear Buyer***

Amit thinks it's challenging to go through each review to decide on quality. He believes a sentiment analysis tool that summarizes reviews would save time in making purchase decisions.

- ***Meera – Ethical Consumer***

Meera wants to know if the brands she purchases from are seen as fair and transparent by other customers. She believes a sentiment analysis tool would provide this information efficiently.

- ***John – Electronic Gadget Enthusiast***

John finds it hard to sort through all reviews for electronics. He thinks a tool that aggregates positive and negative aspects would help him make a better choice.

- ***Vani – Health and Wellness Product Buyer***

Vani values feedback on whether products meet wellness claims. She believes sentiment analysis could help highlight whether customers find the product as effective as advertised.

- ***Ayesha–FashioEnthusiast***

  Ayesha feels that sentiment analysis could show trends in clothing reviews, helping her pick products that customers find stylish and durable.

- ***Raj–Home Improvement Buyer***

Raj wants insights into what homeowners find beneficial about home improvement products. He thinks sentiment analysis would make it easier to identify products that deliver results.

- ***Dr. Kumar–Marke Analyst, Product Research Firm***

Dr. Kumar believes that analyzing customer sentiment on product features helps improve market forecasts. He sees value in using NLP tools for deeper insights into product perceptions.

- ***Maya–Head of Marketing, Retail Chain***

Maya feels that sentiment analysis on customer reviews would allow her team to target marketing efforts on well-received products, maximizing advertising impact.

- ***Ajay–Product Manager, Consumer Goods***

Ajay sees sentiment analysis as a way to highlight the most and least liked features in his products, helping him prioritize improvements and new features.

- ***Radhika–Customer Success Manager, E-commerce Platform***

Radhika thinks sentiment analysis would provide a quick overview of customer satisfaction trends, enabling her to address recurring issues and improve customer experience.

- ***Varun–CEO, Start-up Fashion Brand***

Varun feels sentiment analysis could help him understand customer sentiment around his new fashion line. He believes it would reveal whether his designs meet customer expectations.

- ***Nisha–Social Media Analyst, Food Brand***

Nisha thinks that sentiment analysis could provide insights into customer conversations around her brand, helping her engage with positive and address negative sentiment effectively.

- ***Anand – Head of R&D, Electronics Manufacturer***

Anand feels sentiment analysis could give his team insights into customer pain points with their products, helping them develop features that address these needs.

- ***Snehal – Director of Sales, Skincare Brand***

Snehal believes sentiment analysis could reveal patterns in customer reviews, helping her team understand if products meet customer expectations and how they might enhance appeal.

- ***Tanya – E-commerce Marketplace Owner***

Tanya sees value in analyzing sentiment data across all products on her platform. She believes it would help her guide sellers in improving their offerings.

- ***Ramesh – Data Scientist, Retail Analytics Firm***

Ramesh thinks that sentiment analysis would enhance his data models with insights into customer satisfaction, allowing him to make more accurate sales forecasts.

Here's content similar to your friend's, tailored to fit the objectives of your project, Sentimental Analysis for Product Reviews Using NLP and GenAI.

➢ *End User I: Product Sellers*

Many small-scale product sellers currently lack a dedicated platform that enables them to analyze customer feedback effectively. This limits their ability to understand buyer sentiment and hinders them from adjusting their offerings based on customer preferences. Without access to valuable insights, sellers are often unable to enhance their products or market strategies to better align with buyer expectations, which reduces their potential for growth and customer retention.

Typically, sellers rely on customer reviews scattered across various platforms, making it difficult to gauge consistent feedback trends. With no streamlined tool to process and analyze this feedback, they struggle to identify key themes such as quality, usability, or value that impact customer satisfaction. This absence of organized sentiment analysis prevents sellers from recognizing areas of improvement, ultimately affecting their sales and brand reputation in a competitive market.

Furthermore, sellers face challenges in directly understanding how specific aspects of their products resonate with customers, lacking the communication channels that would allow them to address buyer inquiries and concerns effectively. Without clear feedback analysis, the trust and transparency needed to establish a loyal customer base are limited. This disconnect hinders the ability to cultivate long-term relationships with customers, reducing opportunities for repeat business and long-term brand loyalty.

➢ *End User II: Product Manufacturer*

Manufacturers rely on consistent, detailed feedback to optimize their products and meet customer expectations effectively. However, they often lack a direct channel to access structured insights from customer reviews, which are typically scattered across various platforms. Without a centralized feedback analysis tool, manufacturers struggle to gauge the quality and performance of their products based on customer sentiment, limiting their ability to make timely adjustments that enhance product appeal and reduce production inefficiencies.

Manufacturers also face challenges in product diversification due to limited insights into specific customer preferences across different market segments. Detailed feedback analysis allows them to identify and respond to consumer desires for unique product attributes—such as specific features, durability, or value for money—that can increase market reach. In the absence of effective sentiment analysis, manufacturers cannot readily adjust their production lines to cater to diverse consumer needs, ultimately restricting innovation and competitiveness.

The lack of an efficient feedback system also hinders manufacturers' ability to communicate with both sellers and end customers to discuss feedback-driven improvements, quality concerns, or new product iterations. Without a clear channel to analyze and act upon feedback, the operational efficiency needed for smooth coordination and timely delivery suffers. A dedicated platform for detailed sentiment analysis would enable manufacturers to align more closely with market demand, streamline production adjustments, and foster better relationships with suppliers and customers, driving higher satisfaction and sustained market relevance.

Here's content similar to your friend's, tailored for the context of your Sentimental Analysis for Product Reviews Using NLP and GenAI.

- *End User III: Buyers*

Buyers often struggle to find clear, reliable feedback about product quality, longevity, and user experience when making purchasing decisions online. Without direct access to genuine, well-organized reviews, buyers lack transparency about product performance, which can leave them uncertain about whether their purchases align with their needs and values. This lack of clarity not only reduces consumer confidence but may also lead them to hesitate before making a purchase, as they cannot easily verify the quality or value of the product.

Ethical purchasing is increasingly significant for buyers, who seek products that meet standards of sustainability, ethical sourcing, and transparency. Buyers desire a platform that gives them direct insights into previous customers' experiences and allows them to make informed, responsible purchases. By connecting them to aggregated, sentiment-driven feedback, a sentiment analysis tool can help buyers identify products that meet ethical and quality standards, ensuring their purchases align with their personal values.

Buyers require detailed information on product care, maintenance, and longevity to maximize the value and durability of their purchases. Having access to practical feedback from other users—including insights on product quality and maintenance advice—helps buyers make informed choices and manage their items effectively over time. Access to this feedback not only enables smarter purchasing decisions but also promotes a positive relationship between buyers and sellers, building trust and encouraging repeat purchases as buyers feel more confident in the transparency and reliability of product information.

B. Define

- *Problem Statement:*

The project addresses the challenge of efficiently analyzing and categorizing large volumes of product reviews to provide businesses with actionable insights and help consumers make informed decisions. It aims to simplify user feedback interpretation using natural language processing and visual data representation.

- *Analysis:*

The survey of end-users reveals significant challenges faced by both customers and businesses when dealing with product reviews. Customers often struggle with inconsistency in product quality, misleading or fake reviews, and the sheer complexity of processing vast amounts of feedback. These issues hinder their ability to make well-informed purchasing decisions, resulting in frustration and a lack of trust in online marketplaces.

For businesses, the challenge lies in extracting actionable insights from an overwhelming volume of unstructured review data. Many organizations find it difficult to identify recurring themes and patterns in feedback due to the subjective and often vague nature of user comments. Additionally, delayed or ineffective customer support further exacerbates the negative perception among consumers.

The analysis emphasizes the need for sentiment analysis tools that can address these concerns effectively. By automating the categorization of feedback into positive, negative, and neutral sentiments, such tools simplify the review process for users and help businesses make data-driven improvements. Furthermore, features like filtering reviews by relevance and providing visual summaries enhance user experience and promote transparency.

Overall, the sentiment analysis project aims to bridge the gap between consumer feedback and business strategy, making online marketplaces more user-friendly and responsive. It provides a valuable opportunity for companies to build trust, improve products, and deliver a better shopping experience for their customers.

C. Ideate

➢ *List of Identified Solutions*

- *Sentimental Analysis for Product Reviews Using NLP:*

Enhanced Sentiment Categorization refines the basic sentiment categories (positive, negative, and neutral) by adding levels such as "highly positive" or "mildly negative." This provides more nuanced insights into customer sentiment, allowing businesses to better understand the intensity of feedback. By using sentiment scoring techniques, each review receives a precise categorization that reflects customer emotions accurately. Businesses can use these insights to prioritize customer feedback and address specific concerns. The enhanced categorization would be applied automatically during sentiment analysis, ensuring consistency. This addition empowers businesses to gain a more detailed view of customer satisfaction and helps them make more targeted improvements.

- *Real-Time Sentiment Analysis*

Real-Time Sentiment Analysis enables businesses to monitor customer opinions as new reviews are posted. With this feature, sentiment analysis runs continuously, allowing companies to detect and respond to shifts in sentiment immediately. For example, if a product update receives unexpected negative feedback, real-time monitoring lets the business address the issue quickly. Implemented by automating data ingestion and sentiment analysis, this solution offers constant updates on customer sentiment trends, which companies can leverage for faster and more informed decision-making.

- *Aspect-Based Sentiment Analysis*

Aspect-Based Sentiment Analysis breaks down customer reviews by specific product attributes, such as quality, price, and usability. Instead of only understanding the overall sentiment, this method allows businesses to see what customers think about specific product features. Using NLP techniques like named entity recognition, the system identifies product aspects in each review and analyzes the sentiment for each. Businesses can then target improvements based on which features receive the most criticism or praise. This solution provides actionable insights into product aspects, guiding companies on where to focus their efforts.

- *Customer Feedback Prediction*

Customer Feedback Prediction uses machine learning to forecast future sentiment trends based on past review data. By analyzing historical patterns, this tool helps businesses anticipate customer opinions and proactively address potential issues. If feedback trends indicate increasing customer dissatisfaction, for instance, the business can investigate and make changes before problems escalate. This predictive feature offers a forward-looking perspective, enabling businesses to stay ahead in addressing customer needs and ensuring continuous improvement.

- *Sentiment-Based Response Automatio*

Sentiment-Based Response Automation assists businesses in engaging with customers by generating suggested responses based on the detected sentiment. Positive reviews could prompt an automatic thank-you message, while negative reviews might trigger an apology with a request for further feedback. This feature can improve customer relations by making businesses responsive and attentive to customer concerns.

➢ *Discription of the Best Solutions*

- *Sentimental Analysis for Product Reviews Using NLP:*

The solution offers a more sophisticated method of analyzing customer sentiment than the standard positive, negative, and neutral categories. By introducing additional levels such as "highly positive," "mildly positive," "mildly negative," and "highly negative," this approach allows for a more granular understanding of the emotional intensity behind customer feedback. In your project, where sentiment analysis is performed on product reviews, this categorization can be implemented by assigning sentiment scores to each review using a sentiment analysis tool like TextBlob, which already provides polarity scores. This enhanced categorization would provide businesses with a clearer view of customer emotions, allowing them to identify key trends, such as an increase in highly positive feedback after a product improvement, or a rise in mildly negative sentiment that may require attention. In practical terms, this would improve the ability to track not just whether a product is performing well, but also the degree to which customers are satisfied or dissatisfied. By implementing this solution in your project, the resulting insights would be more actionable businesses can use highly positive feedback for targeted marketing or address mildly negative sentiments before they escalate, helping to maintain a positive brand image and improve customer satisfaction. Additionally, these more nuanced sentiment categories could be visualized in your existing charts, giving businesses a comprehensive overview of not just the frequency of sentiments but also the intensity, helping them make data-driven decisions with greater confidence.

- *Pseudocode:*

```
# Import necessary libraries
IMPORT requests, pandas, BeautifulSoup, nltk, TextBlob, matplotlib, seaborn, WordCloud, streamlit

# Define helper functions
DEFINE get_headers():
   RETURN headers for web scraping

 DEFINE get_reviews_url():
   RETURN Amazon product reviews URL

 DEFINE reviewsHtml(url, len_page):
   soups = []
   FOR page_no IN range(1, len_page + 1):
      FETCH HTML data using requests
      PARSE with BeautifulSoup
      soups.append(parsed_data)
   RETURN soups

 DEFINE get_reviews_data(html_data):
   data_dicts = []
   FOR each review_box IN html_data:
      EXTRACT details (name, stars, title, date, description)
      data_dicts.append(extracted_data)
   RETURN data_dicts

 DEFINE clean_data(df_reviews):
   REMOVE special characters
   CONVERT to lowercase
   REMOVE stop words
   APPLY lemmatization
   SAVE cleaned data to CSV
   RETURN cleaned DataFrame

 DEFINE analyze_sentiment(description):
   polarity = TextBlob(description).sentiment.polarity
   IF polarity > 0:
      RETURN 'Positive', confidence
   ELIF polarity < 0:
      RETURN 'Negative', confidence
   ELSE:
      RETURN 'Neutral', confidence

 DEFINE train_data(df_reviews):
   APPLY analyze_sentiment to each review description
   RETURN DataFrame with sentiment and confidence

 DEFINE visualize_data(df_reviews):
   GENERATE bar charts, pie charts, histograms, word clouds
 # Main application workflow
 DEFINE main():
   DISPLAY Streamlit UI
   IF user selects "Import CSV":
      PROCESS uploaded file
      PERFORM sentiment analysis and visualization
   ELIF user selects "Write Review":
      ANALYZE user-provided review
   ELIF user selects "Enter Amazon URL":
      SCRAPE reviews from URL
      CLEAN and analyze data
```

```
        DISPLAY results
 # Entry point
  IF __name__ == "__main__":
      EXECUTE main()
END
```

➢ *Flow Chart:*

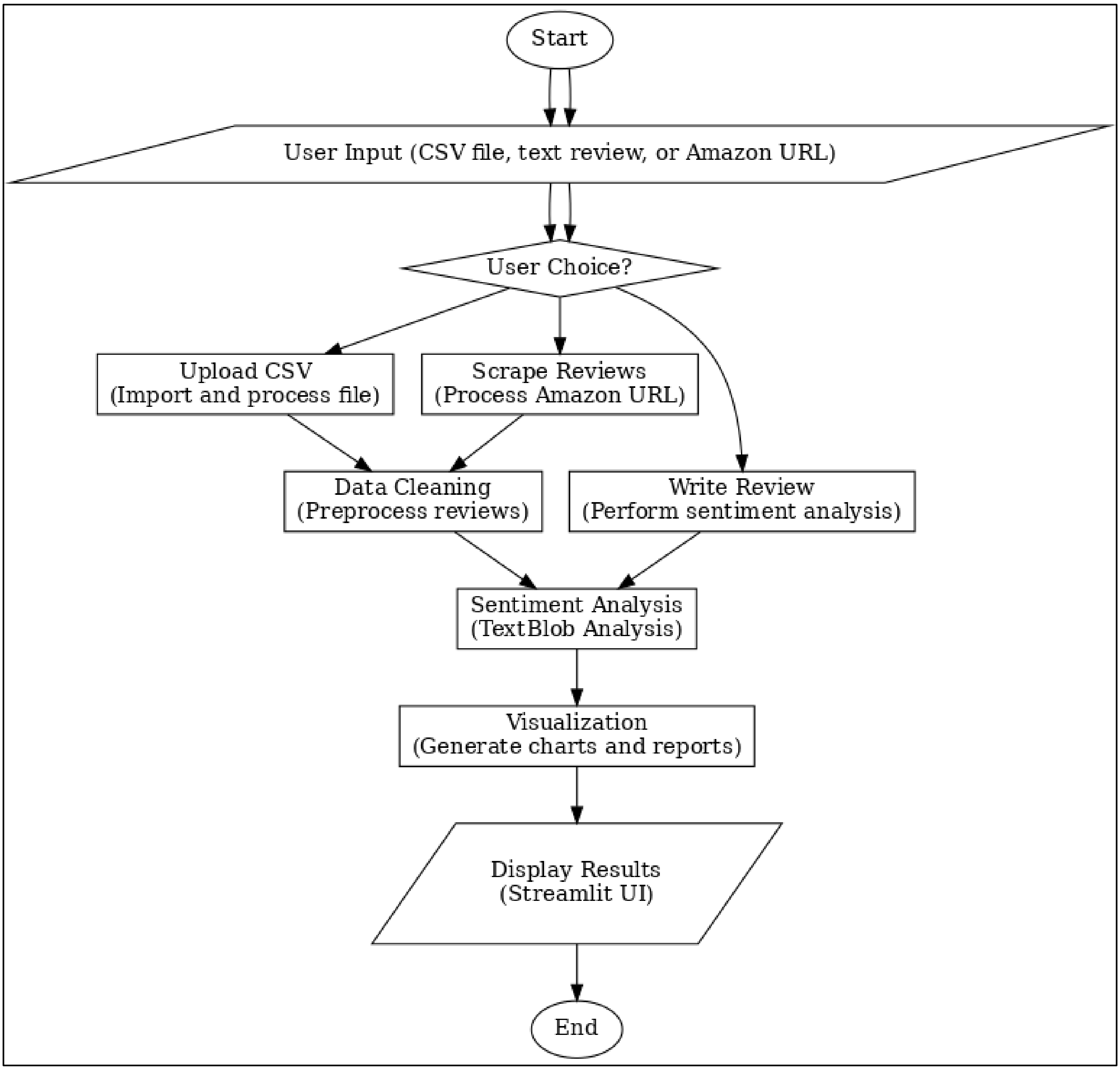

Fig 1: Flow Chart

D. Prototype

➢ *Coding*

```
import requests
import pandas as pd
from bs4 import BeautifulSoup
from datetime import datetime
```

```
import re
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
import nltk
from textblob import TextBlob
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import streamlit as st
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('punkt')

def get_headers():
return {
'authority': 'www.amazon.com',      'accept':
'text/html,application/xhtml+xml,application/xml;q=0.9,image/avif,image/webp,image/apng,*/*;q=0.8,application/signed-
exchange;v=b3;q=0.9',
'accept-language': 'en-US,en;q=0.9,bn;q=0.8',
'sec-ch-ua': '" Not A;Brand";v="99", "Chromium";v="102", "Google Chrome";v="102"',
'user-agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/102.0.0.0
Safari/537.36'
}
def get_reviews_url():
return 'https://www.amazon.com/Fitbit-Smartwatch-Readiness-Exercise-Tracking/product-
reviews/B0B4MWCFV4/ref=cm_cr_dp_d_show_all_btm?ie=UTF8&reviewerType=all_reviews'
def reviewsHtml(url, len_page):
headers = get_headers()
soups = []
for page_no in range(1, len_page + 1):
params = {
'ie': 'UTF8',
'reviewerType': 'all_reviews',
            'filterByStar': 'critical',
            'pageNumber': page_no,
        }
        response = requests.get(url, headers=headers)
        soup = BeautifulSoup(response.text, 'html.parser')
        soups.append(soup)
    return soups

def get_reviews_data(html_data):
    data_dicts = []
    boxes = html_data.select('div[data-hook="review"]')
    for box in boxes:
        try:
            name = box.select_one('[class="a-profile-name"]').text.strip()
        except Exception as e:
            name = 'N/A'
        try:
            stars = box.select_one('[data-hook="review-star-rating"]').text.strip().split(' out')[0]
        except Exception as e:
            stars = 'N/A'
        try:
            title = box.select_one('[data-hook="review-title"]').text.strip()
        except Exception as e:
            title = 'N/A'
        try:
            datetime_str = box.select_one('[data-hook="review-date"]').text.strip().split(' on ')[-1]
            date = datetime.strptime(datetime_str, '%B %d, %Y').strftime("%d/%m/%Y")
```

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```
        except Exception as e:
            date = 'N/A'
        try:
            description = box.select_one('[data-hook="review-body"]').text.strip()
        except Exception as e:
            description = 'N/A'
        data_dict = {
            'Name' : name,
            'Stars' : stars,
            'Title' : title,
            'Date' : date,
            'Description' : description
        }
        data_dicts.append(data_dict)
    return data_dicts

def process_data(html_datas, len_page):
    reviews = []
    for html_data in html_datas:
        review = get_reviews_data(html_data)
        reviews += review
    df_reviews = pd.DataFrame(reviews)
    return df_reviews

def clean_data(df_reviews):
    df_reviews['Description'] = df_reviews['Description'].apply(lambda x: re.sub(r'[^a-zA-Z0-9\s]', '', x))
    df_reviews['Description'] = df_reviews['Description'].apply(lambda x: x.lower())
    stop_words = set(stopwords.words('english'))
    df_reviews['Description'] = df_reviews['Description'].apply(lambda x: ' '.join([word for word in word_tokenize(x) if
word.lower() not in stop_words]))
    lemmatizer = WordNetLemmatizer()
    df_reviews['Description']=df_reviews['Description'].apply(lambda x: ' '.join([lemmatizer.lemmatize(word) for word in
word_tokenize(x)]))
    df_reviews.to_csv('cleaned_reviews.csv', index=False)
    print("Data processing and cleaning completed.")
    return df_reviews
def analyze_sentiment(description):
    analysis = TextBlob(description)
    sentiment = analysis.sentiment.polarity
    subjectivity = analysis.sentiment.subjectivity
    confidence = abs(sentiment) + (1 - subjectivity) * 100
    if sentiment > 0:
        return 'Positive', confidence
    elif sentiment < 0:
        return 'Negative', confidence
    else:
        return 'Neutral', confidence
def train_data(df_reviews):
 df_reviews[['Sentiment','Confidence']] = df_reviews['Description'].apply(analyze_sentiment).apply(pd.Series)
    return df_reviews[['Description', 'Sentiment', 'Confidence']]
def visualize_data(df_reviews):
    st.subheader("Visualized Data:")
    st.subheader("Sentiment Distribution:")
    info_text = '''
            - This visualization represents the distribution of sentiment categories in the reviews.
            - Each bar represents a different sentiment category: Positive, Negative, or Neutral.
            - The size of each bar indicates the proportion of reviews belonging to that sentiment category.
            - For example, if the "Positive" bar is larger, it means there are more positive reviews compared to negative or neutral
ones
    '''
    with st.expander("💡 Info"):
```

```
        st.write(info_text)
    sentiment_counts = df_reviews['Sentiment'].value_counts()
    st.bar_chart(sentiment_counts)
    st.subheader("Pie Chart:")
    visualize_pie_chart(df_reviews)
    st.subheader("Histogram:")

    visualize_histogram(df_reviews)
    st.subheader("Distribution of Review Length:")
    visualize_review_length_distribution(df_reviews)
    st.subheader("Comparison of Sentiment Across Products:")
    compare_sentiment_across_products(df_reviews)
    st.subheader("Time Series Analysis of Product:")
    visualize_time_series(df_reviews)
    st.subheader("Keyword Frequency Analysis:")
    all_words = ' '.join(df_reviews['Description'])
    generate_wordcloud_st(all_words)
def visualize_pie_chart(df_reviews):
    info_text = '''
        - This chart is like a pizza divided into slices.
        - Each slice represents a different sentiment category: Positive, Negative, or Neutral.
        - The size of each slice shows how many reviews fall into that sentiment category.
'''
    with st.expander("💡 Info"):
        st.write(info_text)
    sentiment_counts = df_reviews['Sentiment'].value_counts()
    fig, ax = plt.subplots()
 ax.pie(sentiment_counts,labels=sentiment_counts.index,autopct='%1.1f%%', colors=sns.color_palette('viridis'), startangle=90)
    ax.axis('equal')
    st.pyplot(fig)
def visualize_histogram(df_reviews):
    info_text = '''
        - Imagine stacking blocks to make a bar graph.
        - Each block represents the number of reviews with a specific confidence score.
        - The height of each bar tells us how many reviews have a certain level of confidence in their sentiment analysis.
        - For example, if a bar is tall, it means many reviews have high confidence in their sentiment analysis, while a shorter bar
means fewer reviews have high confidence.
        - This helps us understand the distribution of confidence scores among the reviews.
'''
    with st.expander("💡 Info"):
        st.write(info_text)

    plt.figure(figsize=(10, 6))
    sns.histplot(df_reviews['Confidence'], bins=20, kde=True, color='skyblue')
    plt.title('Distribution of Sentiment Confidence Scores')
    plt.xlabel('Confidence Score')
    plt.ylabel('Frequency')
    st.pyplot()

def analyze_sentiment_st(description):
    analysis = TextBlob(description)
    sentiment = analysis.sentiment.polarity
    subjectivity = analysis.sentiment.subjectivity
    confidence = abs(sentiment) + (1 - subjectivity) * 100
    if sentiment > 0:
        return 'Positive', confidence
    elif sentiment < 0:
        return 'Negative', confidence
    else:
        return 'Neutral', confidence
def generate_wordcloud_st(words):
```

```
    info_text = '''
        - This shows us which words appear most often in the reviews.
        - Think of it as finding the most popular words in a book.
        - The bigger the word in the cloud, the more often it appears in the reviews.
'''
    with st.expander("💡 Info"):
        st.write(info_text)
 wordcloud=WordCloud(width=800,height=400, background_color='white').generate(words)
    fig, ax = plt.subplots(figsize=(10, 6))
    ax.imshow(wordcloud, interpolation='bilinear')
    ax.axis('off')
    st.pyplot(fig)
    st.set_option('deprecation.showPyplotGlobalUse', False)
def visualize_time_series(df):
    info_text = '''
        - Think of this visualization as a tool to see how sentiments (like positivity, neutrality, or negativity) change over time.
        - Imagine a graph with lines showing how people's feelings about the product evolve from day to day.
        - Each line on the graph represents a type of sentiment: positive, neutral, or negative.
        - The horizontal line represents dates, so you can see how sentiments change over different days.
        - The vertical line shows the number of reviews, giving an idea of how many people feel a certain way each day.
        - This graph helps us understand if people's feelings about something are changing over time.
'''
    with st.expander("💡 Info"):
        st.write(info_text)
    df['Date'] = pd.to_datetime(df['Date'], format="%d/%m/%Y")
    # df['Date'] = pd.to_datetime(df['Date'])
   df['Sentiment']=pd.Categorical(df['Sentiment'],categories=['Negative','Neutral', 'Positive'], ordered=True)
  df_time_series=df.groupby([pd.Grouper(key='Date',freq='D'),

'Sentiment']).size().unstack(fill_value=0)
    df_time_series.plot(kind='line', stacked=True, figsize=(10, 6))
    plt.title('Sentiment Over Time')
    plt.xlabel('Date')
    plt.ylabel('Number of Reviews')
    st.pyplot()

def visualize_review_length_distribution(df):

    info_text = '''
        - Think of this visualization as a way to understand the distribution of review lengths.
        - Review length refers to the number of words in each review.
        - Frequency in this context means how often reviews of different lengths occur.
        - Imagine a line graph where the length of the line at each point represents the frequency of reviews with a specific length.
        - Longer parts of the line mean more reviews are that length, while shorter parts mean fewer reviews are that length.
        - For example, if you see a tall peak in the graph, it means many reviews are of that length, while a flat area indicates fewer
reviews of that length.
        - This helps us understand how long or short the reviews are on average and how common reviews of different lengths are.
'''
    with st.expander("💡 Info"):
        st.write(info_text)

    df['Review Length'] = df['Description'].apply(lambda x: len(x.split()))
    plt.figure(figsize=(10, 6))
    sns.histplot(df['Review Length'], bins=20, kde=True, color='skyblue')
    plt.title('Distribution of Review Length')
    plt.xlabel('Review Length')
    plt.ylabel('Frequency')
    st.pyplot()

def compare_sentiment_across_products(df):
    info_text = '''
```

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```
        - This visualization compares the sentiment of reviews for different products.
        - Imagine comparing how people feel about various items or services.
        - Each bar on the chart represents the number of positive, negative, and neutral reviews for each product.
        - For example, if you see a tall blue section (positive sentiment) on a bar, it means many reviews for that product are
positive.
        - This comparison helps us understand the overall sentiment distribution across different products.
'''
    with st.expander("💡 Info"):
        st.write(info_text)

 sentiment_counts_by_product= df.groupby('Name')['Sentiment'].value_counts().unstack(fill_value=0)
    sentiment_counts_by_product.plot(kind='bar', stacked=True, figsize=(10, 6))
    plt.title('Sentiment Comparison Across Products')
    plt.xlabel('Product')
    plt.ylabel('Number of Reviews')
    st.pyplot()

def visualize_keyword_frequency(df):
    info_text = '''
        - This shows us which words appear most often in the reviews.
        - Think of it as finding the most popular words in a book.
        - The bigger the word in the cloud, the more often it appears in the reviews.
'''
    with st.expander("💡 Info"):
        st.write(info_text)
    all_words = ' '.join(df['Description'])
 wordcloud=WordCloud(width=800,height=400, background_color='white').generate(all_words)
    plt.figure(figsize=(10, 6))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    st.pyplot(
def import_data(file_path):
    df = pd.read_csv(file_path)
    return df
def clean_and_store_data(df, csv_filename='cleaned_reviews.csv'):
    # Clean data
    df['Description'] = df['Description'].apply(lambda x: re.sub(r'[^a-zA-Z0-9\s]', '', x))
    df['Description'] = df['Description'].apply(lambda x: x.lower())
    stop_words = set(stopwords.words('english'))
     df['Description'] = df['Description'].apply(lambda x: ' '.join([word for word in word_tokenize(x) if word.lower() not in
stop_words]))
    lemmatizer = WordNetLemmatizer()
    df['Description']=df['Description'].apply(lambda x: ' '.join([lemmatizer.lemmatize(word) for word in word_tokenize(x)]))
    # Store cleaned data in a new CSV
    cleaned_csv_path = csv_filename
    df.to_csv(cleaned_csv_path, index=False)
    return cleaned_csv_path
def main():
    st.title("SentiMart🎁: Amazon Sentiment App")
    option = st.sidebar.selectbox("Choose an option", ["Write Review", "Enter Amazon URL", "Import CSV"])
    if option == "Import CSV":
        st.header("Import CSV for Analysis")
        uploaded_file = st.file_uploader("Upload your CSV file", type=["csv"])
        if uploaded_file is not None:
            df = pd.read_csv(uploaded_file)
df[['Sentiment','Confidence']] = df['Description'].apply(analyze_sentiment_st).apply(pd.Series)
            st.subheader("Data Preview:")
            st.write(df.head())
            st.subheader("Visualized Data:")
            st.subheader("Sentiment Distribution:")
            info_text = '''
```

```
            This visualization represents the distribution of sentiment categories in the reviews.
           Each bar represents a different sentiment category: Positive, Negative, or Neutral.
            The size of each bar indicates the proportion of reviews belonging to that sentiment category.
            For example, if the "Positive" bar is larger, it means there are more positive reviews compared to negative or neutral
ones
        '''
        with st.expander("💡 Info"):
            st.write(info_text
        sentiment_counts = df['Sentiment'].value_counts()
        st.bar_chart(sentiment_counts)
        st.subheader("Pie Chart:")
        visualize_pie_chart(df
        st.subheader("Histogram:")
        visualize_histogram(df)
        st.subheader("Distribution of Review Length:")
        visualize_review_length_distribution(df)
                st.subheader("Comparison of Sentiment Across Products:")
        compare_sentiment_across_products(df)
        st.subheader("Time Series Analysis of Product:")
        visualize_time_series(df)

        st.subheader("Keyword Frequency Analysis:")
        visualize_keyword_frequency(df)

  elif option == "Write Review":
      st.header("Write Review for Analysis")
      user_input = st.text_area("Enter your review:")
      if st.button("Analyze"):
          if user_input:
              result, confidence = analyze_sentiment_st(user_input)
              st.subheader("Sentiment Analysis Result:")
              st.write(f"Sentiment: {result}")
              st.write(f"Confidence Score: {confidence}")
          else:
              st.warning("Please enter a review for analysis.")
  elif option == "Enter Amazon URL":
      st.header("Enter Your Favourite Amazon product's URL")
      try:
          URL_input = st.text_input("Enter Valid Amazon URL:")
      except ValueError as e:
          st.warning("Error: "+e)
      page_len = st.slider("Select the number of pages to scrape", min_value=1, max_value=10, value=1)

      if st.button("Analyze"):
          if URL_input:
              html_datas = reviewsHtml(URL_input, page_len)
              df_reviews = process_data(html_datas, page_len)
              df_reviews = clean_data(df_reviews)
              cleaned_csv_path = clean_and_store_data(df_reviews)
              df_cleaned = import_data(cleaned_csv_path)
              df_cleaned[['Sentiment','Confidence']]= df_cleaned['Description'].apply(analyze_sentiment_st).apply(pd.Series)
              st.subheader("Data Preview after Cleaning:")
              st.write(df_cleaned.head())
              visualize_data(df_cleaned)
          else:
              st.warning("Please enter a URL first!")
if __name__ == "__main__":
  main
```

➢ *Screenshot of the Project Demo and its Description*

Fig 2: Home Page

➢ *Home Page*

Where users are invited to write and analyze product reviews for sentiment classification. A text box allows for easy review input, followed by an "Analyze" button to initiate processing. The sidebar offers navigation options, and the clean, minimal design enhances usability.

Fig 3: Home Page Options

➤ *Home Page Options*

The homepage with a sidebar menu offering three options: "Write Review," "Enter Amazon URL," and "Import CSV." Users can choose their preferred method for inputting product reviews. The main section remains focused on the review analysis, ensuring a clear and organized interface.

Fig 4: Review Analysis Page

➤ *Review Analysis Page*

The Review Page, where users can enter a product review in the provided text box. An "Analyze" button initiates sentiment analysis. The sidebar on the left features options for review input, including writing a review, entering an Amazon URL, or importing a CSV file.

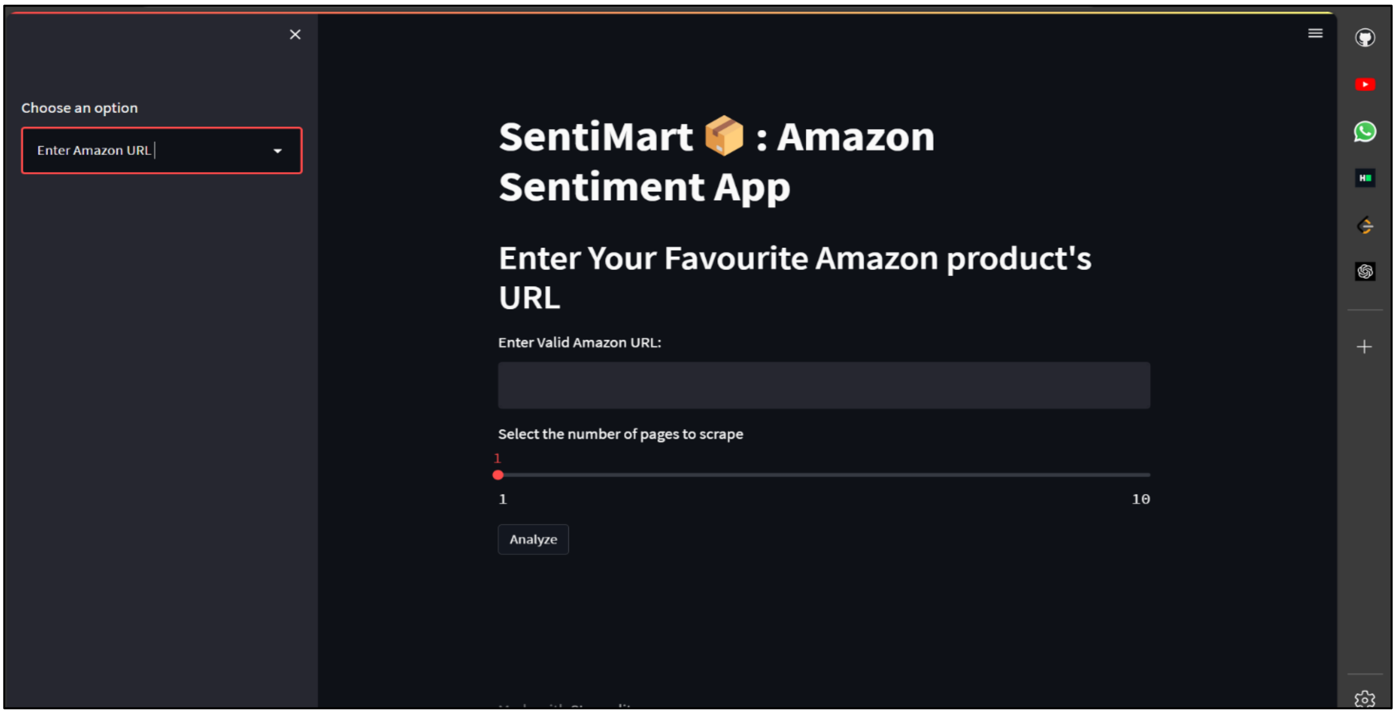

Fig 5: Product URL Analysis Page

➢ *Product URL Analysis Page*

The Product URL Analysis Page, where users can input an Amazon product URL for sentiment evaluation. The main area features a text field for entering the URL, along with an "Analyze" button to begin the analysis. The sidebar offers additional options, such as writing a review or importing data via CSV, making the tool versatile for different review input methods.

Fig 6: Import CSV Page

➢ *Import CSV Page*

It allows users to import a CSV file, with a file size limit of 200MB, for analysis. Users can drag and drop their CSV files or browse to select one. The interface is built using Streamlit and has a clean, dark-themed design.

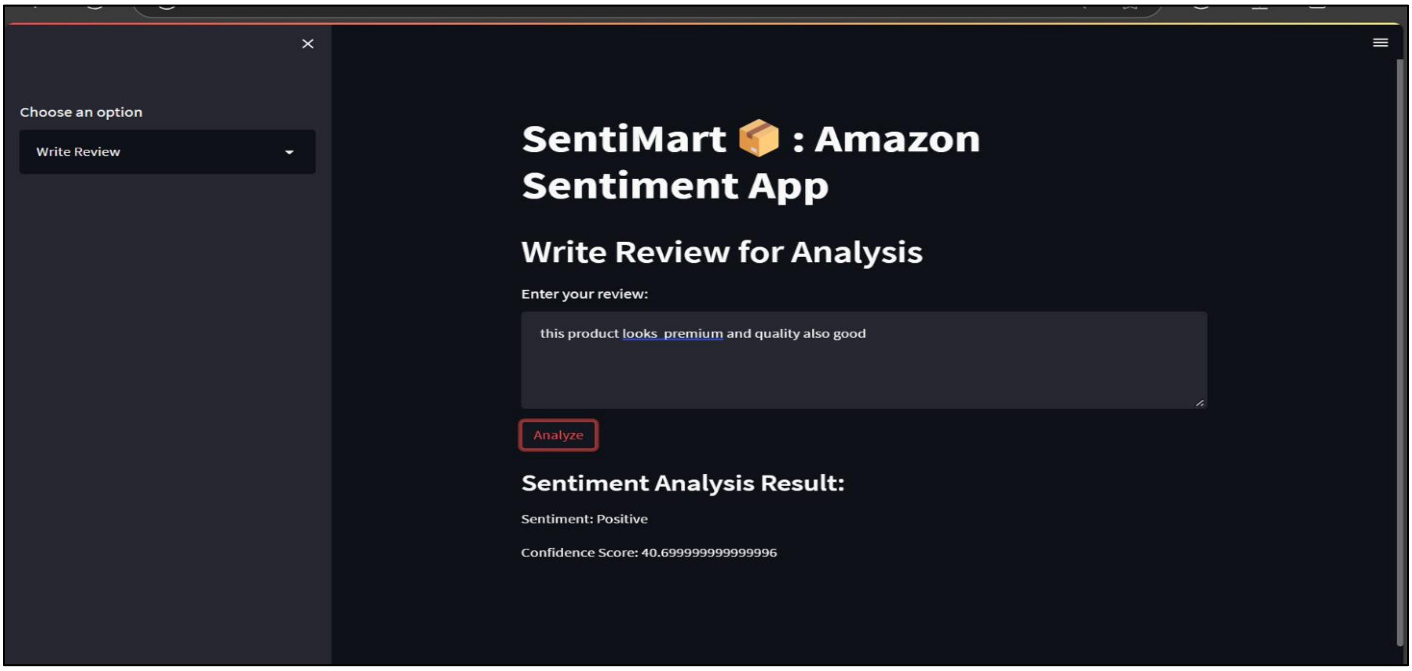

Fig 7: Review Result

➢ *Review Result*

The entered review is, "this product looks premium and quality also good," which, after clicking "Analyze," yields a positive sentiment result. The confidence score for this sentiment analysis is approximately 40.7. This interface provides a simple way to assess the tone of product reviews.

Fig 8: Uploading CSV File

➢ *Uploding CSV File*

Uploading a CSV file named "flipkart_reviews (1).csv" for analysis. The file, with a size of 1.9KB, has been successfully uploaded, and a preview of the data is displayed below. The preview shows product names, starting with "Candes 12 L Room/Personal Air Cooler" in various colors and descriptions. This data preview helps users confirm the contents of the file before running sentiment analysis.

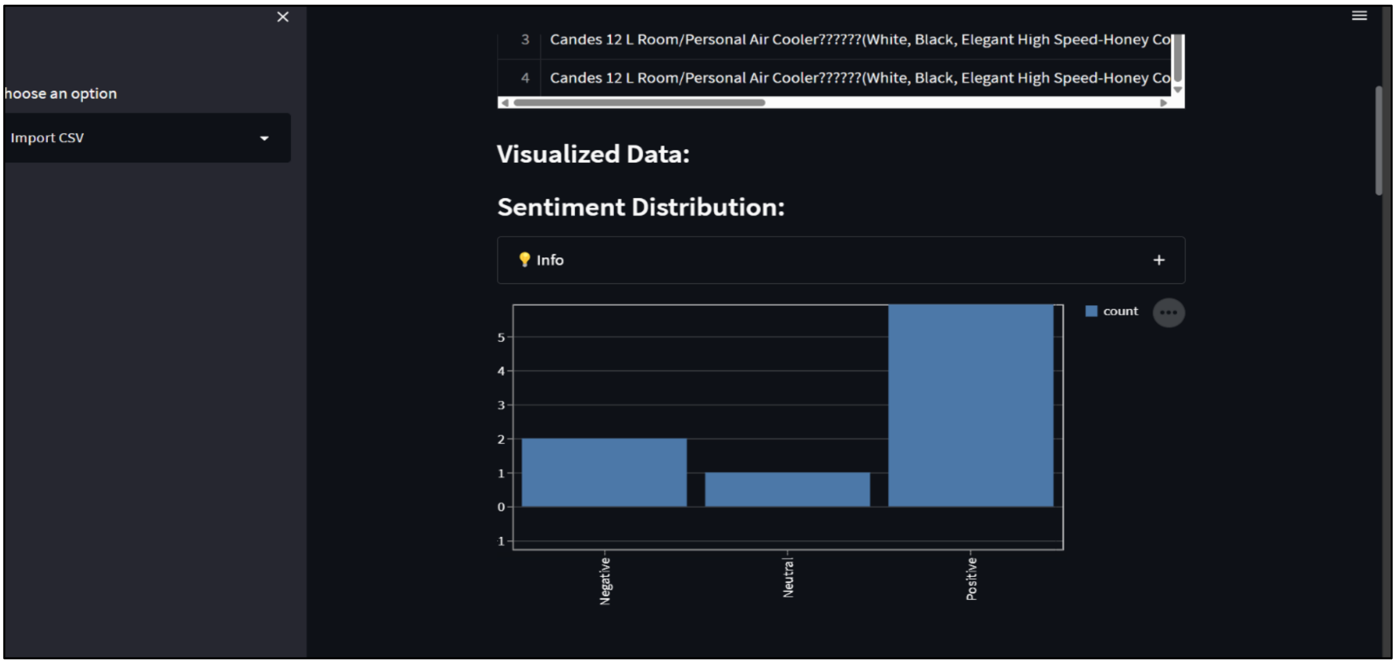

Fig 9: Bar Chart Visualization

➢ *Bar Chart Visualization*

The results of product review analysis. After analyzing the uploaded CSV file, a bar chart visualizes the sentiment distribution across the reviews, with categories for Negative, Neutral, and Positive sentiments. The chart indicates that most reviews are positive, followed by a few negative and neutral reviews. This summary helps in quickly assessing the overall customer sentiment towards the products.

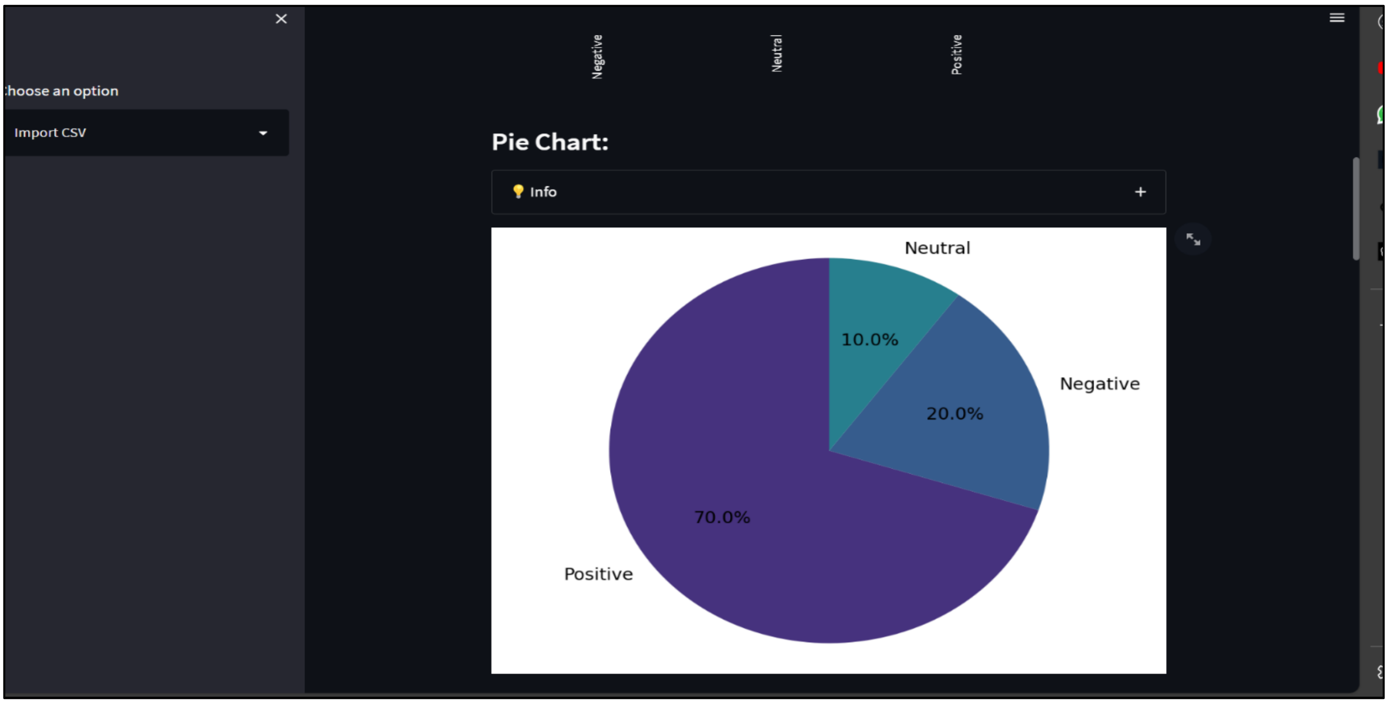

Fig 10: Pie Chart Visualization

➢ *Pie Chart Visualization*

In a pie chart, it would display the proportions of Negative, Neutral, and Positive reviews as segments of a circle. Each segment's size would represent the relative frequency of each sentiment category, making it easy to see the dominant sentiment at a glance. For example, if Positive reviews are the majority, they would take up the largest portion of the chart, while smaller segments would represent Neutral and Negative reviews. This format provides a quick, visual overview of customer sentiment distribution.

CHAPTER FOUR
TESTING AND MAINTENANCE

A. Testing Use Cases:

Test case id	Module	Description	Precondition s	Test steps	Expected result	Status
1	Sentiment Analysis	Verify accurate sentiment for product	Sample Product reviews available	Load sample product reviews	Reviews categrozied Into positive,negative	Pass
2	Sentiment Analysis	Verify handling of mixed sentiment reviews	Mixed sentiment review	1.Load a review with both positive and negative 2.Run the sentiment Analysis	Review categorized as Mixed or appropriately divided	Pass
3	NLP Processing	Verify accurate tokenization	Review data with different word structures	Process the review using NLP tokenization	Review is split into individual tokens correctly,without errors	Pass
4	Sentiment Scoring	Verify sentiment score calculation	Positive Review data available	Load a positive review	Sentiment score indicates high	Pass
5	Dashboard	Verify visualization of sentiment analysis in the dashboard	Sentiment results generated	1.Negative to the sentiment analysis 2.Check for Pie chart or other visualization	Sentiment categories are correctly displayed in visual format	Pass
6	Real-Time Analysis	Verify real-time sentiment assigned to specific product attributes	Review with multiple product aspects	Run the aspect-based sentiment analysis	Sentiment is correctly attributed to each product aspect(e.g,Positive for quality,negative for price)	Pass
7	Aspect-Based Sentiment	Verify correct sentiment assigned to specific product attributes	Review with multiple product aspects	Load a review mentioning multiple aspects like price and quality	Sentiment is correctly attribute to each product aspect	Pass
8	User Interaction	Verify suggestion of response for negative	Positive review posted	Load a positive review. Uses the sentiment based response automation	Appropriate response Is suggested	Pass
9	User Integration	Verify suggestion of responses for positive reviews	Negative review posted	Load a negative review Uses the sentiment-based response	Appropriate response is suggested	Pass
10	Performance	Verify system Performance when processing a larger number of reviews	Large dataset of reviews	Load large dataset of reviews Run the sentiment analysis model	The System processes as well reviews without performance degradation or errors	Pass

B. Maintenance

- *Scraping Amazon Reviews*

- Description: The function `reviewsHtml()` scrapes product reviews from Amazon based on the provided product URL and page length.

- *Maintenance Task:*

- Test Case 1: Verify the functionality of the review scraping after Amazon website updates.
- Action: Test scraping functionality on different Amazon product pages to ensure the correct extraction of review data.
- Expected Outcome: Reviews should be correctly extracted across different pages without failure.
- Test Case 2: Check that the correct number of pages is scraped.
- Action: Verify that the number of pages scraped matches the input from the user.
- Expected Outcome: The correct number of pages (as per the user's slider input) should be scraped.

- *Data Extraction and Processing*

- Description: The `get_reviews_data()` function extracts review metadata like the reviewer's name, rating, title, date, and description.

- *Maintenance Tasks:*

- Test Case 1: Verify the extraction of review metadata.
- Action: Test the extraction process on different Amazon review pages to ensure all fields (name, stars, title, date, description) are being extracted accurately.
- Expected Outcome: All review data should be properly captured and stored in a structured format.
- Test Case 2: Handle missing data gracefully.
- Action: Check how the system handles missing or malformed review data (e.g., missing stars or name fields).
- Expected Outcome: Missing data should be handled gracefully (e.g., filled with 'N/A' or appropriate default values)

- *Data Cleaning*

- Description: The `clean_data()` function removes non-alphanumeric characters, converts text to lowercase, and removes stopwords.

- *Maintenance Tasks:*

- Test Case 1: Validate text cleaning after updates to external libraries (like `nltk`).
- Action: Run a variety of review samples through the cleaning process to ensure that special characters are removed and text is normalized.
- Expected Outcome: The reviews should be cleaned correctly with unwanted characters removed, and text should be in lowercase without stopwords.
- Test Case 2: Check for accurate lemmatization and tokenization.
- Action: Test that words are correctly lemmatized (e.g., "running" becomes "run") and tokenized.
- Expected Outcome: All words should be properly processed, with meaningful tokens retained.

- *Sentiment Analysis*

- Description: The `analyze_sentiment()` function applies sentiment analysis to the review descriptions to classify reviews as Positive, Neutral, or Negative.

- *Maintenance Tasks:*

- Test Case 1: Verify sentiment classification accuracy after library updates (TextBlob).
- Action: Run a set of test reviews through the sentiment analysis function to ensure they are classified correctly.
- Expected Outcome: Reviews should be classified as Positive, Neutral, or Negative with a reasonable level of confidence.
- Test Case 2: Check confidence scores for consistency.
- Action: Review a range of sentiment values and ensure the confidence scores are correctly calculated.

- Expected Outcome: Confidence scores should reflect the polarity and subjectivity of the sentiment analysis, with higher values indicating greater certainty.

➢ *Data Visualization*

- Description: The `visualize_data()` function generates multiple visualizations such as sentiment distribution, pie charts, histograms, and word clouds.

➢ *Maintenance Tasks:*

- Test Case 1: Check the rendering of all charts (e.g., bar charts, pie charts, histograms) after updates to plotting libraries (Matplotlib, Seaborn).
- Action: Test the visualizations on sample data to ensure that all charts render correctly, including bar charts for sentiment distribution and pie charts for sentiment proportion.
- Expected Outcome: Visualizations should display correctly with proper labels, legends, and titles.
- Test Case 2: Validate the word cloud functionality.
- Action: Check that the word cloud accurately represents the frequency of words in reviews.
- Expected Outcome: The word cloud should display frequent words in larger font sizes, visually representing popular keywords.

➢ *Time Series Analysis*

- Description: The `visualize_time_series()` function generates a time series analysis of product reviews based on sentiment over time.
- Maintenance Tasks:
- Test Case 1: Verify that time series analysis works for different date formats and review frequencies.
- Action: Test on various products to ensure that reviews are aggregated correctly by date, and sentiment is accurately shown over time.
- Expected Outcome: Time series should show sentiment trends over time, with proper categorization of review sentiment.

➢ *Sentiment Comparison Across Products*

- Description: The `compare_sentiment_across_products()` function compares sentiment distribution across multiple products.

➢ *Maintenance Tasks:*
- Test Case 1: Verify correct sentiment comparison across different products.
- Action: Test this feature with multiple products to ensure the comparison chart displays correctly.
- Expected Outcome: The chart should compare sentiment across products with correct visualization of positive, negative, and neutral reviews.

➢ *Review Length Distribution*

- Description: The `visualize_review_length_distribution()` function plots the distribution of review lengths across all reviews.

➢ *Maintenance Tasks:*

- Test Case 1: Check the distribution of review lengths on a variety of datasets.
- Action: Validate that the review length histogram displays properly, representing the distribution of review lengths across a given dataset.
- Expected Outcome: The histogram should show review length distributions, indicating whether reviews are typically short, medium, or long.

➢ *Data Import and Export*

- Description: The `import_data()` and `clean_and_store_data()` functions handle the importing and exporting of review data.

➢ *Maintenance Tasks:*

- Test Case 1: Verify the correct import and export of CSV files.
- Action: Test importing a variety of clean and raw CSV files and exporting them after cleaning to ensure the CSV handling works as expected.

- Expected Outcome: Data should be correctly imported, cleaned, and exported as CSV files without data loss.

➢ *Streamlit App Integration*

- Description: The Streamlit app integrates all functionalities into a user-friendly interface, where users can input Amazon URLs or import CSV files for analysis.

➢ *Maintenance Tasks:*

- Test Case 1: Verify all Streamlit widgets (text input, sliders, buttons) work as expected.
- Action: Test the Streamlit widgets for user interaction to ensure they respond correctly (e.g., URL input, page length selection, CSV upload).
- Expected Outcome: All user inputs should be processed without errors, and the corresponding visualizations should appear as expected.
- Test Case 2: Ensure the application runs smoothly with various browsers and platforms.
- Action: Test the app on different browsers (Chrome, Firefox, Edge) and platforms (Windows, macOS) to ensure compatibility.
- Expected Outcome: The app should run smoothly and render correctly on all supported platforms and browsers.

CHAPTER FIVE
RESULT

The Amazon Review Sentiment Analysis project helps businesses understand customer feedback by categorizing reviews into positive, negative, or neutral sentiments. It scrapes Amazon reviews or imports CSV data, cleanses the text, and applies sentiment analysis using TextBlob. The tool provides insightful visualizations like bar charts, pie charts, and word clouds to represent sentiment distribution, review confidence, and frequent keywords. It also offers time series analysis and sentiment comparison across products. The interactive Streamlit interface makes it user-friendly, allowing businesses to make data-driven decisions, enhance products, and address customer concerns effectively through actionable insights.

CHAPTER SIX
CONCLUSION & FUTURE WORK

In conclusion, the Amazon Review Sentiment Analysis project serves as a powerful and versatile tool for businesses seeking to understand customer opinions and enhance their products or services. By analyzing customer feedback from Amazon, this project provides valuable insights into sentiment trends, helping companies gauge how their products are perceived in the market. The ability to gather review data either through web scraping or CSV file imports adds flexibility, making it suitable for a variety of use cases. The project's data cleaning process ensures that the reviews are preprocessed effectively for accurate sentiment analysis, while TextBlob delivers reliable sentiment categorization and confidence scores. The visualizations, including bar charts, pie charts, word clouds, and time-series analysis, offer a comprehensive view of sentiment distribution, allowing businesses to make informed decisions based on real customer sentiments. The interactive interface built with Streamlit enhances the user experience, enabling users to easily upload data, analyze reviews, and interpret the results. Overall, this project equips businesses with the tools to monitor customer feedback, identify potential issues, and improve product offerings, ultimately fostering better customer satisfaction and informed decision-making. It serves as an essential resource for leveraging customer sentiment to drive growth and success in a competitive marketplace.

- *Future Work*

For future work, the Amazon Review Sentiment Analysis project can be further enhanced in several ways to provide even more value to businesses and users. First, expanding the sentiment analysis capabilities by integrating more advanced Natural Language Processing (NLP) models, such as BERTZ or GPT, could improve the accuracy of sentiment categorization, especially for nuanced or mixed sentiment reviews. Additionally, incorporating a multilingual support feature would allow the tool to analyze reviews in various languages, making it useful for global product analysis. Enhancing the data scraping function to handle dynamic Amazon pages, including products with infinite scroll or CAPTCHA protection, would also improve the tool's robustness. Furthermore, adding a feature to track sentiment trends over time for specific products or brands would provide valuable insights into how customer perceptions evolve, helping businesses identify potential issues or opportunities earlier. Integrating external data sources, such as social media sentiment or customer support feedback, would allow businesses to get a more holistic view of customer opinions. Lastly, incorporating predictive analytics and recommendation systems could enable the tool to forecast potential changes in sentiment based on historical data, helping businesses anticipate customer reactions to product updates or marketing strategies. These improvements would significantly increase the project's utility for businesses looking to stay ahead in the competitive market.

ANNEXURE

- JOURNAL CERTIFICATE
- CONFERENCE CERTIFICATE

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