Sentiment Analysis Web Application : A New Paradigm for business intelligence

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GitHub Link

Abstract:

A potent tool for analyzing and interpreting sentiment represented in textual data is the sentiment analysis web app. The sentiment analysis web tool provides businesses with a significant solution given the growing significance of comprehending customer sentiment, market trends, and brand reputation. The app offers insights into customer opinions, preferences, and satisfaction levels by utilizing natural language processing techniques and machine learning algorithms. Users may evaluate massive amounts of data, track sentiment in real-time, and receive useful insights for sensible decision-making through an accessible user interface. In today's data-driven business environment, this abstract emphasizes the importance of the sentiment analysis web app in increasing customer experiences, optimizing marketing efforts, and upholding a favorable brand image.

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1. Introduction

Problem Statement:

Developing a sentiment analysis web app to address the challenge of understanding and analyzing sentiment expressed in textual data across various domains and platforms.

Problem Description:

Businesses and organizations face the difficulty of comprehending and interpreting the sentiment behind vast amounts of textual data generated through social media, customer reviews, feedback forms, and other sources. Extracting valuable insights from this data is crucial for making informed decisions, improving customer experiences, and managing brand reputation. However, manually processing and analyzing such extensive text data is time-consuming and error-prone.

There is a need for an automated solution that can accurately analyze sentiment, classify text as positive, negative, or neutral, and provide actionable insights to businesses and individuals. The sentiment analysis web app aims to address this problem by leveraging machine learning and natural language processing techniques to automate sentiment analysis tasks and deliver accurate and real-time sentiment analysis results.

Key Features:

1. **User Interface:** The web application will feature a user-friendly interface that enables seamless interaction between users and the program. It should have a straightforward layout that makes it simple for users to input text data and get sentiment analysis findings.

2. **Text Input:** Users should be able to enter the text they wish to analyze in the app's text input area. Users can insert one or more texts for sentiment analysis using its capability for multiple inputs.

3. **Sentiment Analysis:** Sentiment analysis is the primary feature of the online application. To assess the sentiment of the supplied text, it should use a trained machine learning model or natural language processing methods. The text should be correctly classified as having a positive, negative, or neutral sentiment by the sentiment analysis algorithm.

4. **Visualization of Results:** The app should clearly and attractively display the sentiment analysis results. It can display the sentiment distribution or offer a sentiment score for the input text using graphs, charts, or other visualization approaches.

5. **Performance and Scalability:** The web app should be designed to handle a significant volume of text data and provide real-time or near-real-time sentiment analysis results. It should be scalable, ensuring smooth performance even with an increasing number of users or data inputs.

6. **Security and Privacy:** To protect user data and maintain privacy, the web app should implement appropriate security measures. It should employ data encryption, secure communication protocols, and follow best practices for user authentication and authorization.

7. **Responsive Design:** The web application should be responsively developed so that it can adjust to various screen sizes and devices. The best possible user experience is thus guaranteed on PCs, tablets, and mobile devices.

8. **Deployment and Maintenance:** The web application should be simple to deploy on a web server and maintain. To guarantee seamless operation and user satisfaction, routine updates, bug repairs, and speed optimizations should be made.

Overall, the goal of the sentiment analysis web app is to offer a user-friendly, effective, and secure platform for text data sentiment analysis. It gives users the ability to extract useful information from textual content, without any understanding of Programming empowering them to base judgements on the findings of sentiment analysis.

2. Market niche and target Customers

The market niche and target customers for a sentiment analysis web app can vary based on specific focus areas and customization options.

Below are some potential market niches and target customers :

1. **Social Media Management:**

   Target social media managers, digital marketing agencies, and businesses that heavily rely on social media platforms for brand monitoring, reputation management, and customer sentiment analysis.

2. **Customer Experience and Feedback Management:**

   Cater to companies that prioritize customer satisfaction and experience, such as e-commerce platforms, customer support teams, and service-oriented businesses. They can leverage sentiment analysis to gain insights from customer feedback and enhance their products or services accordingly.

3. **Brand Reputation and Crisis Management:** Focus on businesses that are concerned about maintaining a positive brand image and need to monitor sentiment trends, detect potential crises, and manage brand reputation effectively. This can include PR agencies, brand managers, and companies in industries prone to public opinion volatility.

4. **Market Research and Competitive Intelligence:** Target market research firms, consultants, and businesses that require sentiment analysis to gain insights into market trends, consumer behavior, and competitive positioning. This can aid in making informed business decisions and identifying new opportunities.

5. **Media and Entertainment Industry:** Serve media outlets, content creators, and entertainment companies that want to gauge audience sentiment, measure the success of campaigns, track public opinion on movies or TV shows, and optimize content strategies.

6. **Financial Services and Investment Analysis:** Cater to financial institutions, investment firms, and analysts who require sentiment analysis to monitor market sentiment, analyze news and social media for investment decisions, and track sentiment towards specific financial instruments or companies.

7. **Product Development and User Feedback:** Target businesses in the software development industry or those with a focus on product development. They can use sentiment analysis to gather user feedback, measure user satisfaction, and prioritize product enhancements.

8. **Academic and Research Institutions:** Serve universities, research institutions, and scholars conducting studies on sentiment analysis, natural language processing, and social sciences. They may require advanced sentiment analysis tools and APIs for their research and academic projects.

3. Financial Modelling

1. Identify which Market your product/service will be launched into:

A Sentiment Analysis Web Application can be introduced into several markets due to its wide-ranging applicability. These markets include:

a) E-Commerce: E-commerce businesses can use the application to analyze customer reviews and feedback on their products or services. This can help them understand customer sentiment and improve their offerings accordingly.
b) Social Media Monitoring: Social media platforms and businesses using social media for marketing can benefit from sentiment analysis. By understanding public sentiment towards their brand, product, or service, they can adjust their strategies and respond to concerns more effectively.
c) Customer Service: Businesses can apply sentiment analysis to customer support interactions to better understand the sentiments and emotions of their customers. This can help improve customer satisfaction and service quality.
d) Market Research: Market research firms can use sentiment analysis to understand public opinion on various topics, trends, and brands. This can aid in providing more accurate insights and forecasts.
e) Healthcare: In the healthcare sector, sentiment analysis can be used to understand patient feedback and improve healthcare services.
f)Media and Entertainment: Media and entertainment companies can use sentiment analysis to gauge audience reactions to various shows, movies, events, and more.
g) Public Relations and Reputation Management: Businesses can use sentiment analysis to monitor public sentiment towards their brand, allowing them to manage their reputation more effectively.
h) Financial Services: Financial institutions and fintech companies can use sentiment analysis to understand investor sentiment, which can influence stock prices and trading decisions.

b. Collect some data /statistics regarding that Market Online

1. Market Growth: The global sentiment analysis market size was valued at USD 4.1 billion in 2020 and is expected to expand at a compound annual growth rate (CAGR) of 20.2% from 2021 to 2028 (Grand View Research).

2. Key Industries: E-commerce, BFSI, retail, and healthcare are among the major industries where sentiment analysis software is extensively used. For instance, in the e-commerce sector, sentiment analysis is used to understand customer feedback and improve product recommendations.

3. Adoption Rate: A survey conducted by Deloitte showed that 83% of companies have already implemented or are planning to implement solutions for text analysis within the next two years, which includes sentiment analysis.

4. Application in Social Media: According to SproutSocial, 48% of marketers agreed that social listening increased in importance in 2021, indicating a rising demand for sentiment analysis tools that can interpret social media data.

5. Online Reviews Importance: According to a study by Spiegel Research Center, nearly 95% of shoppers read online reviews before making a purchase, highlighting the importance of sentiment analysis in understanding and leveraging customer reviews.

6. Customer Experience: A report from PwC showed that 32% of customers would stop doing business with a brand they loved after one bad experience. This underscores the significance of sentiment analysis in preempting negative customer experiences.

7. Artificial Intelligence (AI) in Sentiment Analysis: Market Research Future (MRFR) estimates that the AI in social media market will achieve a CAGR of about 28% between 2018 and 2023, suggesting an increased integration of AI in sentiment analysis tools.

8. Demand for Real-Time Analysis: As per a Salesforce report, 70% of customers say connected processes, such as seamless handoffs or contextualized engagement based on earlier interactions, are very important to win their business, indicating the rising demand for real-time sentiment analysis.

c. Design Financial Equation corresponding to that Market Trend

1 Linear financial model :-

Let
y = Total profit
m = Service fee
$x(t)$ = total sales as a function of time.
c = Data production & maintenance cost.

~~Putting these values in following eqn~~

$m = ₹4000$

$\cancel{x(t)}$ $x = 200$

$t = 12$ months.

$c = 10,00,000$ ₹

Put these in

$\boxed{y = m * (x * t) - c}$ → financial equation.

$y = 4000 * (200 \times 12) - 10,00,000$

$y = 4000 \times 2400 - 10,00,000$

$y = 96,00,000 - 10,00,000$

$\boxed{y = 86,00,000}$ INR

2 Exponential market growth :-

Let $X(t)$ = total sales as function of time.
$X(0)$ = initial no. of sales
e = base of natural logarithm.
g = growth rate.
t = time.

So the financial equation will be :-

$\boxed{y = m \times (X(0) \times e^{(g * t)}) - C}$

Now taking same values as before.

$X(0) = 200$, $g = 6.5\%$ (0.065), $m = 4000$, $C = 10,000,000$ ₹, $t = 12$ months.

$y = 4000 \times (200 \times e^{(0.065 \times 12)}) - 10,00,000$

$y = 4000 \times (200 \times 2.03) - 10,00,000$

$y = 16,31,520 - 10,00,000$

$\boxed{y = 6,31,520}$ ₹

4. Target Specifications and Characterization

Target Requirements: Age, gender, location, level of education, income, occupation, marital status, and other demographic data are included.

Firmographics (B2B): Sector, scale of operation, revenue, location, etc.
Information about technology adoption, internet usage patterns, preferred communication methods, etc. Targeted regions, urban or rural locations, regional or global markets, etc. are examples of geographic factors.

Characterization: Interests, values, attitudes, way of life decisions, personality traits, goals, etc. are examples of psychographic qualities. Buying patterns, purchasing power, brand loyalty, product usage, decision-making processes, etc. are examples of behavioral patterns. Challenges, issues, and preferences of the target market that the product or service seeks to address.

5. Prototype Selection

a) Feasibility of Developing a Sentiment Analysis Web Application in the Short-Term Future (2-3 years):

Technological Feasibility:
The development of a sentiment analysis web application is technologically feasible within a 2-3 year timeframe. The necessary machine learning (ML) and natural language processing (NLP) techniques for sentiment analysis are already well-established, with state-of-the-art models like BERT, RoBERTa, and GPT-3 available for use. As technology continues to advance, these techniques will likely become even more refined, enabling more accurate and nuanced sentiment analysis.

Market Feasibility:
The market demand for sentiment analysis tools is strong and growing. Businesses increasingly recognize the value of understanding customer sentiment to drive decision-making and strategy. Given the projected growth of sectors such as e-commerce, social media analytics, and customer experience management, it's feasible to anticipate that a sentiment analysis web application would have substantial market potential within 2-3 years.

Operational Feasibility:
In terms of operations, the creation of a sentiment analysis web application within a 2-3 year period is viable. Building the application will require assembling a skilled team with expertise in areas such as NLP, ML, web development, UX/UI design, and data management. Given the rising number of professionals and resources in these fields, sourcing talent and knowledge should be feasible.

Financial Feasibility:
While development costs will be significant, encompassing personnel, infrastructure, licensing, and other expenses, the potential for return on investment is high given the broad range of potential users. Furthermore, the use of cloud-based services and open-source software can help manage costs. The application could be monetized through various models such as freemium, subscription, or pay-per-use, contributing to financial feasibility.

Legal and Regulatory Feasibility:
The development and use of a sentiment analysis web application must comply with relevant data privacy regulations such as GDPR and CCPA. It is feasible to develop a compliant application, but this will require careful planning and continuous monitoring of evolving legal and regulatory landscapes. Ensuring user consent for data use, anonymizing data, and implementing robust data security measures will be crucial.

b) **Viability: Product/Service should be relevant or able to survive in long term future. (20-30 years) :**

Sentiment Analysis, as a branch of Natural Language Processing (NLP), has significant growth potential and viability over the next 20-30 years, as it is intrinsically tied to the continual expansion and influence of digital communication. Here, we discuss the long-term viability of a sentiment analysis web application from multiple perspectives.

Increasing Online Interactions: With an ever-growing volume of online interactions and digital content, the need to understand and interpret these data sources will also continue to grow. Businesses, governments, researchers, and a broad spectrum of organizations will continue to seek effective tools for analyzing text data, ensuring the relevance of a sentiment analysis web application.

Evolving Technology: Advancements in AI, machine learning, and NLP will enable more sophisticated and accurate sentiment analysis, further driving the long-term applicability of such an application. As these technologies improve, the sentiment analysis web application can incorporate these enhancements to remain relevant and efficient.

Greater Demand for Personalization: The increasing demand for personalized services in sectors like e-commerce, healthcare, and entertainment, requires a deep understanding of customer sentiment. This trend is expected to continue, thereby ensuring the relevance of sentiment analysis.

Increased Use in Various Sectors: The versatility of sentiment analysis means it can be applied across many sectors. Whether for brand monitoring, political sentiment analysis, customer service automation, or mental health analysis, the potential applications are vast and growing. As such, the longevity of sentiment analysis web applications is highly promising.

Support Decision Making: In the age of data-driven decision making, sentiment analysis serves as a crucial tool, helping to understand public opinion and trends. This can inform strategies in a variety of sectors, from marketing to policy-making, maintaining the long-term need for such tools.

c) **Monetization: Product/Service should be monetizable directly :**

A sentiment analysis web application can offer significant value to businesses and organizations across various sectors. Monetizing such an application can be achieved through a variety of strategies:

Subscription Model: Users pay a monthly or annual fee to gain access to the sentiment analysis tool. Different tiers can be offered with varying features, such as the volume of text that can be analyzed, access to advanced analytics, or real-time sentiment tracking.

Freemium Model: Users can access basic features of the sentiment analysis tool for free but need to pay for premium features such as in-depth sentiment analytics, priority data processing, or customizable sentiment categories.

Pay-As-You-Go Model: Users pay based on the amount of data they process through the sentiment analysis tool. This model can be attractive for businesses that have fluctuating volumes of data to analyze.

Enterprise Model: Larger businesses or organizations might require more advanced features, such as integration with existing data infrastructure, customization to specific use-cases, or dedicated customer support. These users can be served with a more expensive enterprise package.

Data Consulting Services: In addition to the sentiment analysis tool, you can offer data consulting services. This could include providing detailed sentiment reports, offering advice on interpreting the sentiment data, or helping businesses integrate the sentiment data with their other data sources.

Advertising: If the web application attracts a significant number of users, advertising could be a potential source of revenue. However, this would need to be balanced against the potential impact on the user experience.

Partnerships: Forming partnerships with other businesses that could benefit from sentiment analysis, such as market research firms or customer relationship management (CRM) platforms, could open up additional revenue streams.

6. **Business Model (Monetization Idea)**

Monetization Strategy	Description
Subscription Model	Offer tiered subscription plans with different features and usage limits. This could include access to advanced sentiment analysis models, real-time data processing, API access, or additional customization options.
Pay-per-Use Model	Charge users based on the volume of data processed or the number of sentiment analysis tasks performed. This model allows flexibility for users with varying needs and usage patterns.
Enterprise Licensing	Provide enterprise-level licenses for businesses that require sentiment analysis at scale. Tailor the pricing based on the number of users, data volume, and specific enterprise requirements.
White-labeling	Offer the option for businesses to white-label the sentiment analysis web app, allowing them to customize and rebrand it as their own sentiment analysis solution. Charge a licensing fee or revenue sharing arrangement for white-labeled versions.
API Access	Provide an API (Application Programming Interface) that allows developers to integrate sentiment analysis capabilities into their own applications, platforms, or systems. Charge based on API usage, data volume, or request limits.

Monetization Strategy	Description
Partnerships and Collaborations	Establish partnerships or collaborations with other companies or platforms that can benefit from sentiment analysis. This could involve revenue-sharing arrangements, joint marketing efforts, or offering bundled services.
Advertisement Placement	Consider displaying targeted advertisements within the sentiment analysis web app, based on user demographics, sentiment trends, or user preferences. Ad revenue can be generated through partnerships with advertisers.
Freemium Model	Offer a basic version of the sentiment analysis web app for free, with limited features or usage. Then, provide premium features or additional functionalities through subscription or one-time purchase options.

7. Concept Development (Brief summary of Product/Service will be developed)

Businesses may analyze and evaluate sentiment conveyed in textual data with the help of the robust sentiment analysis web app. The app uses machine learning algorithms and natural language processing techniques to extract insightful information about user preferences, attitudes, and satisfaction levels. Users may evaluate massive amounts of data, track sentiment in real-time, and receive useful insights for making educated decisions with the help of an intuitive user interface.

Real-time sentiment monitoring, customizable dashboards, sentiment trend analysis, sentiment-based alerts, data visualization, and connection with social media platforms are some of the main features of the sentiment analysis web app. With the help of these tools, organizations can better manage customer sentiment, monitor brand reputation, improve customer experiences overall, and optimize marketing efforts.

The sentiment analysis web app caters to various industries and target customers, including social media managers, digital marketing agencies, customer support teams, market research firms, brand managers, financial institutions, content creators, and academic institutions. By providing a comprehensive and user-friendly solution for sentiment analysis, the app aims to assist businesses in making data-driven decisions, improving customer satisfaction, and maintaining a positive brand image in today's data-driven business landscape.

Through continuous refinement and validation based on market demand and user feedback, the sentiment analysis web app aims to be a valuable and indispensable tool for businesses seeking to understand and leverage sentiment analysis for their strategic decision-making processes.

8. Product details

a. How does it work ?

The sentiment analysis web app utilizes natural language processing (NLP) techniques and machine learning algorithms to analyze text and determine sentiment. The typical workflow involves the following steps:

a. **Data Collection**: Gather textual data from various sources such as social media, customer reviews, surveys, and other relevant sources.

b. **Preprocessing:** Clean and preprocess the text by removing noise, punctuation, and stopwords, and performing tasks like tokenization and stemming.

c. **Feature Extraction:** Extract relevant features from the text, such as n-grams, word embeddings, or other linguistic features that capture sentiment-related information.

d. **Sentiment Classification:** Apply machine learning algorithms, such as Naive Bayes, Support Vector Machines, or deep learning models like Recurrent Neural Networks or Transformers, to classify the sentiment of each text snippet as positive, negative, or neutral.

e. **Result Visualization:** Present the sentiment analysis results through intuitive dashboards, visualizations, or reports.

b. Data Sources

For the sentiment analysis web app, a diverse range of datasets from various sources were utilized to train and validate the sentiment analysis models.

The following AmazonAWS Open dataset was used in this process:

The dataset being downloaded from https://s3.amazonaws.com/text-datasets/imdb.npz is the Internet Movie Database (IMDB) movie reviews sentiment analysis dataset. This is one of the most widely used and referenced datasets for sentiment analysis tasks and is included as part of the Keras deep learning library.

The IMDB movie reviews dataset consists of 50,000 movie reviews, which are split evenly with 25,000 reviews intended for training and 25,000 for testing. Each set consists of 50% negative and 50% positive reviews, thus providing a balanced dataset for sentiment analysis tasks.

The reviews have been preprocessed, with each review encoded as a sequence of word indexes. These word indexes are integers where each integer maps to a specific word in a dictionary. The dictionary can be built from the training dataset, mapping each unique word in the reviews to a unique integer. The order of the sequences corresponds to the order of the words in the original sentences.

The sentiment expressed in the reviews forms the label or target for each example. A sentiment of 0 refers to a negative sentiment while a sentiment of 1 refers to a positive sentiment.

This dataset is often used for binary classification tasks, where the goal is to accurately predict whether a given review expresses positive or negative sentiment. It is commonly used in training and benchmarking models based on various machine learning and deep learning algorithms, including but not limited to Naive Bayes, Support Vector Machines, and Recurrent Neural Networks.

c. Algorithms, Frameworks, Software, etc. Needed

The development of a sentiment analysis web app may require the following:

- **Programming languages:** Python, Java, or R for developing the backend algorithms and models.

- **Natural Language Processing (NLP) libraries:** NLTK, spaCy, or CoreNLP for text preprocessing and feature extraction.

- **Machine learning frameworks:** scikit-learn, TensorFlow, or PyTorch for implementing sentiment classification models.

- **Web development frameworks:** Flask, Django, or Node.js for building the web app's frontend and backend.

- **Database systems:** MySQL, PostgreSQL, or MongoDB for storing and retrieving data.

- **Visualization libraries:** Matplotlib, Seaborn, or D3.js for creating visualizations and dashboards.

d. Team Required to Develop

The development team for a sentiment analysis webapp may consist of the following roles:

- Project Manager
- Data Scientist/NLP Engineer
- Backend Developer
- Frontend Developer
- UX/UI Designer
- Database Administrator
- Quality Assurance Engineer

e. What does it cost?

The cost of developing a sentiment analysis web app can vary depending on factors such as the complexity of the project, the team size, the technology stack used, and any additional customization or integration requirements. It is advisable to consult with development agencies or obtain cost estimates from development teams to get a more accurate understanding of the specific costs involved.

Additionally, ongoing costs may include hosting fees, data storage costs, and maintenance and support expenses.

9. Prototype Development on small Scale

a. Importing Necessary Libraries:

```python
#Import Libraries
import numpy
from numpy import array
from keras.datasets import imdb
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM, Dropout
from keras.layers import Embedding
from keras.preprocessing import sequence
from keras.models import load_model
import re
import numpy as np
from nltk.tokenize import word_tokenize
import nltk

# fix random seed for reproducibility
numpy.random.seed(7)
```

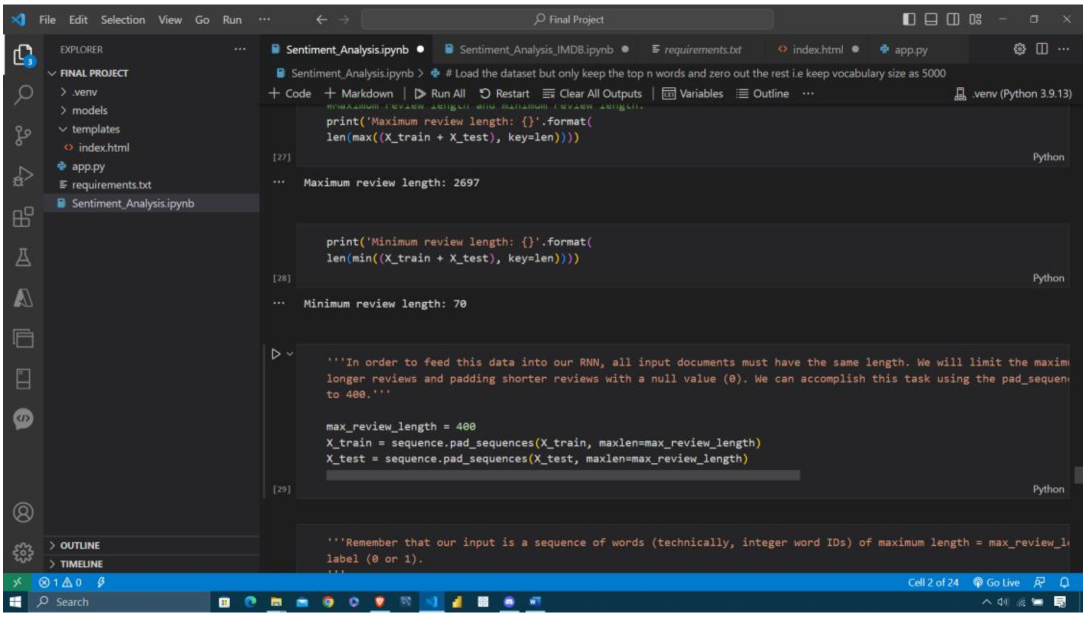
Python

b. Loading the data :

```python
# Load the dataset but only keep the top n words and zero out the rest i.e keep vocabulary size as 20000
top_words = 20000 #vocabulary_size = 5000
(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words=top_words)
```

Python

```
Downloading data from https://s3.amazonaws.com/text-datasets/imdb.npz
17465344/17464789 [==============================] - 0s 0us/step
```



c. ML Modelling using "Hard Sigmoid" activation function :

```
'''Remember that our input is a sequence of words (technically, integer word IDs) of maximum length = max_review_l
label (0 or 1).
'''
# create the model
embedding_vecor_length = 100
model = Sequential()
model.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
model.add(Dropout(0.25))
model.add(LSTM(80))
model.add(Dropout(0.1))
model.add(Dense(1, activation='hard_sigmoid'))

'''We first need to compile our model by specifying the loss function and optimizer we want to use while training,
we'd like to measure. Specify the appropriate parameters, including at least one metric 'accuracy'.'''
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=30, batch_size=70)
```
Python

Sentiment_Analysis.ipynb > # Load the dataset but only keep the top n words and zero out the rest i.e keep vocabulary size as 5000

+ Code + Markdown | Run All Restart Clear All Outputs | Variables Outline ... .venv (Python 3.9.13)

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_3 (Embedding)     (None, 400, 100)          2000000

 dropout_6 (Dropout)         (None, 400, 100)          0

 lstm_3 (LSTM)               (None, 80)                57920

 dropout_7 (Dropout)         (None, 80)                0

 dense_3 (Dense)             (None, 1)                 81

=================================================================
Total params: 2058001 (7.85 MB)
Trainable params: 2058001 (7.85 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
Epoch 1/30
358/358 [==============================] - 657s 2s/step - loss: 0.5668 - accuracy: 0.7132 - val_loss: 0.4157 - val_acc
Epoch 2/30
358/358 [==============================] - 468s 1s/step - loss: 0.4048 - accuracy: 0.8412 - val_loss: 0.4007 - val_acc
Epoch 3/30
358/358 [==============================] - 474s 1s/step - loss: 0.5063 - accuracy: 0.7725 - val_loss: 0.6231 - val_acc
Epoch 4/30
358/358 [==============================] - 497s 1s/step - loss: 0.4943 - accuracy: 0.7986 - val_loss: 0.3899 - val_acc
Epoch 5/30
```

```
#Calculate Accuracy
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```
Python

```
Accuracy: 75.37%
```

d. ML Modelling using "Hard Sigmoid" activation function with some changes in vector length, dropout rate, LSTM units :

```
embedding_vecor_length = 110 # Increased the vector_length
model_1 = Sequential()
model_1.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
model_1.add(Dropout(0.5))  # Increase dropout rate to 0.5
model_1.add(LSTM(100))       # Increases LSTM units
model_1.add(Dropout(0.2))  # Reduce dropout rate to 0.2
model_1.add(Dense(1, activation='hard_sigmoid'))

model_1.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model_1.summary())
model_1.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=30, batch_size=50)


#Calculate Accuracy
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

model_1.save('Hard_Sigmoid_model_1.h5')  # Save the model
```
Python

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_6 (Embedding)     (None, 400, 110)          2200000

 dropout_12 (Dropout)        (None, 400, 110)          0

 lstm_6 (LSTM)               (None, 100)               84400

 dropout_13 (Dropout)        (None, 100)               0

 dense_6 (Dense)             (None, 1)                 101

=================================================================
Total params: 2284501 (8.71 MB)
Trainable params: 2284501 (8.71 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
Epoch 1/30
500/500 [==============================] - 812s 2s/step - loss: 0.5446 - accuracy: 0.7450 - val_loss: 0.5572 - val_acc
Epoch 2/30
500/500 [==============================] - 869s 2s/step - loss: 0.7307 - accuracy: 0.7405 - val_loss: 0.5140 - val_acc
Epoch 3/30
500/500 [==============================] - 867s 2s/step - loss: 0.5007 - accuracy: 0.7749 - val_loss: 0.5298 - val_acc
Epoch 4/30
500/500 [==============================] - 870s 2s/step - loss: 0.4057 - accuracy: 0.8419 - val_loss: 0.5252 - val_acc
```

```
500/500 [==============================] - 843s 2s/step - loss: 0.0829 - accuracy: 0.9860 - val_loss: 1.4616 - val_acc
Epoch 28/30
500/500 [==============================] - 871s 2s/step - loss: 0.1193 - accuracy: 0.9802 - val_loss: 1.2933 - val_acc
Epoch 29/30
500/500 [==============================] - 869s 2s/step - loss: 0.0578 - accuracy: 0.9914 - val_loss: 1.4968 - val_acc
Epoch 30/30
500/500 [==============================] - 861s 2s/step - loss: 0.0673 - accuracy: 0.9884 - val_loss: 1.0953 - val_acc
Accuracy: 75.37%
```

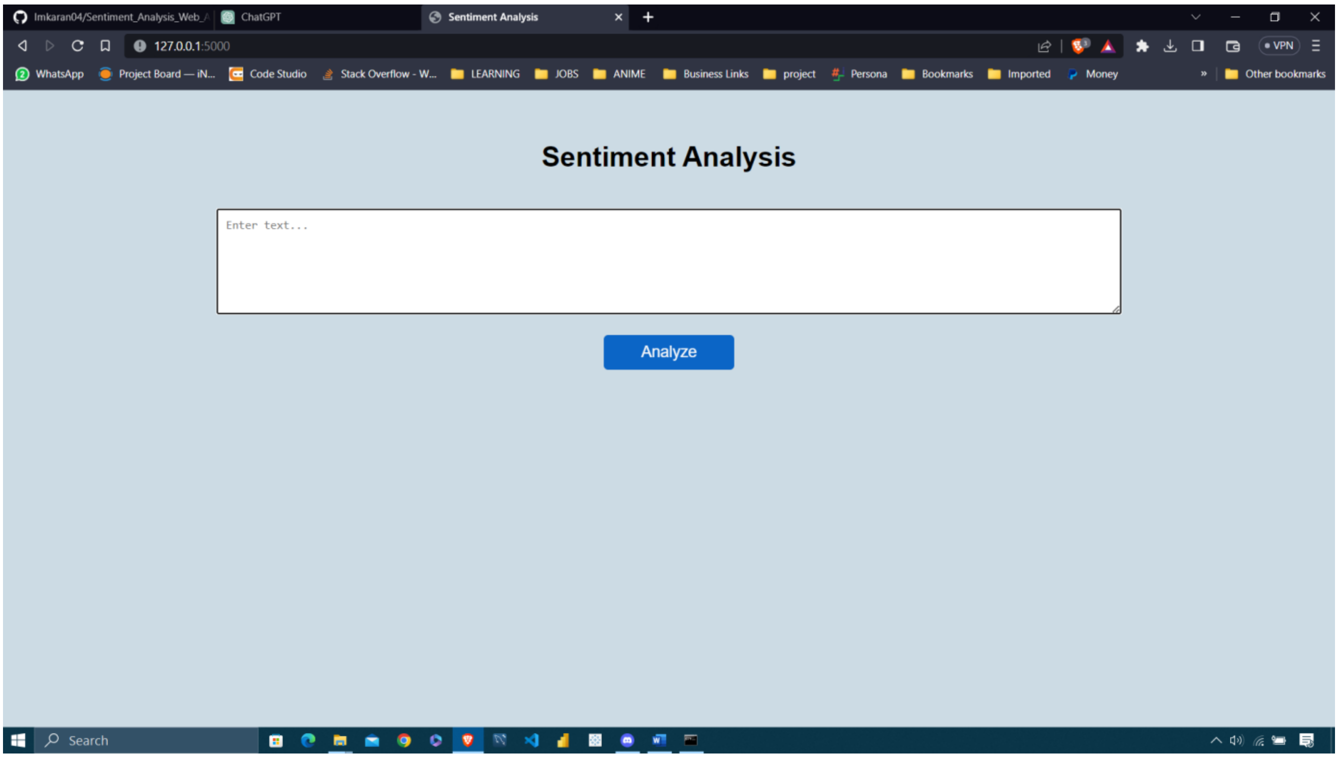
e. ML Modelling using “Sigmoid” activation function with adding 1 more LSTM layer :

```python
# Added 1 more LSTM layer

embedding_vecor_length = 100
model = Sequential()
model.add(Embedding(top_words, embedding_vecor_length, input_length=max_review_length))
model.add(Dropout(0.25))
model.add(LSTM(80, return_sequences=True))
model.add(LSTM(80))

model.add(Dropout(0.20))
model.add(Dense(1, activation='sigmoid'))

'''We first need to compile our model by specifying the loss function and optimizer we want to use while training,
we’d like to measure. Specify the appropriate parameters, including at least one metric ‘accuracy’.'''
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
print(model.summary())
model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=20, batch_size=50)

#Calculate Accuracy
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))

model.save('sigmoid_model_2.h5')  # Save the model
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_8 (Embedding)     (None, 400, 100)          2000000

 dropout_15 (Dropout)        (None, 400, 100)          0

 lstm_10 (LSTM)              (None, 400, 80)           57920

 lstm_11 (LSTM)              (None, 80)                51520

 dropout_16 (Dropout)        (None, 80)                0

 dense_7 (Dense)             (None, 1)                 81

=================================================================
Total params: 2109521 (8.05 MB)
Trainable params: 2109521 (8.05 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
None
Epoch 1/20
500/500 [==============================] - 469s 933ms/step - loss: 0.4530 - accuracy: 0.7919 - val_loss: 0.3617 - val_
Epoch 2/20
500/500 [==============================] - 477s 955ms/step - loss: 0.2439 - accuracy: 0.9075 - val_loss: 0.3363 - val_
Epoch 3/20
500/500 [==============================] - 520s 1s/step - loss: 0.1592 - accuracy: 0.9436 - val_loss: 0.3372 - val_acc
Epoch 4/20
```

```
500/500 [==============================] - 524s 1s/step - loss: 0.0247 - accuracy: 0.9929 - val_loss: 0.6761 - val_acc
Epoch 17/20
500/500 [==============================] - 585s 1s/step - loss: 0.0195 - accuracy: 0.9945 - val_loss: 0.7880 - val_acc
Epoch 18/20
500/500 [==============================] - 510s 1s/step - loss: 0.0249 - accuracy: 0.9924 - val_loss: 0.9276 - val_acc
Epoch 19/20
500/500 [==============================] - 487s 974ms/step - loss: 0.0231 - accuracy: 0.9927 - val_loss: 0.7510 - val_
Epoch 20/20
500/500 [==============================] - 520s 1s/step - loss: 0.0127 - accuracy: 0.9960 - val_loss: 0.8854 - val_acc
Accuracy: 84.64%
```

d. User-Interface :



10. Conclusion

In conclusion, the sentiment analysis web app provides users with a powerful tool for analyzing the sentiment of text data. By leveraging machine learning models or natural language processing algorithms, the app can accurately classify text as expressing positive, negative, or neutral sentiment. The user-friendly interface, advanced analysis options, and visualization of results enhance the user experience and provide valuable insights into the sentiment of the text.

The web app's scalability ensures it can handle large volumes of text data and deliver real-time or near-real-time sentiment analysis results. The implementation of security and privacy measures safeguards user data and maintains confidentiality. The responsive design ensures a seamless experience across different devices.

By offering user management features, such as account creation and analysis history, the web app allows users to save and access their analyzed results, providing convenience and personalization. Additionally, the web app's deployment and maintenance considerations ensure its ongoing functionality and optimal performance.

Overall, the sentiment analysis web app serves as a valuable tool for businesses, researchers, and individuals to gain insights from text data, enabling them to make informed decisions and understand sentiment trends. It opens up opportunities for sentiment analysis in various domains, such as customer feedback analysis, social media monitoring, and market research.

11. External Search (online information sources/references/links)

1. **"Sentiment Analysis and Opinion Mining" by Bing Liu: "https://www.cs.uic.edu/~liub/publications/KDD2007-opinion-mining.pdf"**

2. **"A Survey of Sentiment Analysis Techniques and Applications" by Gokulakrishnan Srinivasan and Lakshmi D: "https://arxiv.org/abs/1805.04966 ".**

4. **"Sentiment Analysis: A Deep Learning Approach" by Xiaodan Zhu et al.: "https://arxiv.org/abs/1708.01509".**

5. **"Sentiment Analysis: Techniques, Applications and Challenges - A Survey" by Sanjana Sahu and Aswani Kumar Cherukuri: "https://arxiv.org/abs/1904.02229" .**