Sentiment Analysis on Product Reviews: Amazon

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Certificate

It is certified that the contents and the form of this report titled "Sentiment Analysis on Product Reviews: Amazon" submitted by **Muhammad Naeem Ur Rehman** (17-SE-01), **Aimma Zia** (17-SE-09), **Muhammad Zubair Iqbal** (17-SE-51) and **Muhammad Mahad Shahid** (17-SE-53) have been found satisfactory for the requirement of degree.

Supervisor's Signature: ________________________________

Dr. Ali Javed

Dedication

To one Lord

ALLAH Almighty

And

To our Parents, Teachers and Mentors

Acknowledgement

We would like to thank our Supervisor **Dr. Ali Javed** who showed complete trust in our project. He cooperated with us with every level. He was always available for any sort of guidance and actively participated in giving suggestions to improve overall performance of project. After that we would like to thank our parents and well-wishers who prayed for our success.

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CHAPTER 01: INTRODUCTION

The terms sentiment analysis and opinion mining were created by Nasukawa and Yi (2003) and Dave et al., respectively (2003). The branch of research that examines people's views, evaluations, feelings, attitudes, and emotions in written text is known as sentiment analysis and opinion mining. It has also been usually studied in web mining, data mining and information retrieval. Some people get confused with the term's sentiment and opinion, there's not a distinct difference between these two terms but a basic definition is provided just for understanding. So, sentiment is defined as an attitude, thought, or judgment prompted by feeling, whereas opinion is a view, judgment, or appraisal. The field represents a large problem space. We use sentiment analysis to help us understand trends in products, services, organizations, individuals, events, issues, topics or reviews. Sentiment analysis currently encompasses a wide range of related terms and tasks, including sentiment analysis, opinion mining, opinion analysis, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, and review mining.

Sentiment analysis is a field of study that arose from the study of social media on the internet. Since 2002, there has been a lot of activity in the field of sentiment analysis research. Sentiment analysis is an essential tool for extracting and using information from social media. It aids us in comprehending the rise of social network and sentiment analysis, as well as their applications in the digital world.

The challenge now a days is useful for amazon seller as they will know what the short-comings of the product are and another very prime objective that lies within sentiment analysis of amazon product is for the new sellers as new sellers are emerging day by day so they can surf to the best seller reviews and can see what people are most liking in their product and what are the things they are disliking or the things in which they want improvement. This helps the seller as they do not have to go through the survey process either online or on ground, they simply must run our model on the product reviews and later can introduce their very new product in the market with ease. This anticipated and analyzed records can be used to recognize the general repute of corporations; of how they are caring for their customers. We can certainly determine various styles of the usage of information mining algorithms according to our requirements.

1.1 Project Goal:

Have you ever written a review to share your thoughts on a product or service? And do you have a practice of reading online reviews before purchasing a product? Have you ever read a product's or service's reviews or ratings before purchasing it? Then you've almost certainly encountered sentiment analysis. This type of information is useful not only to you, but also to businesses. Assume you work for a firm that sells a range of goods. You want to know the features of your best-selling items and, more importantly, why they're so popular. Then there's sentiment analysis, which is based on product reviews. In this Project, we will make sense of the sentiment expressed in product review section of Amazon. We will help the seller through our model so that he/she knows how the customers are feeling about their product, in this way seller can improve the area of product which needs to be improvised or think of ways to make it better for customer use. On customer point of view, customer will know what the general sentiments of the product are, in simple words I would say the “true quality” of the product.

Project goal in one liner would be that we will drive traffic to ones’ product in the listing of amazon products or seller’s investment based on our analysis.

1.2 Aims and Objectives:

- In the given document of reviews from Amazon product find sentiments of each review.
- A model trained on previous (labelled) data and achieve an initial test accuracy around 85 - 90%.
- Scrape the data and fed it to the pre trained neural network.
- An interactive website for dashboard creation.
- To provide insights or general sentiments about the product to seller as well as customer.
- To provide insights of the product in the customer’s hand to seller.
- Investment in the product by the seller based on our model.

1.3 Deliverables:

The deliverables of Sentiment Analysis on Product Reviews: Amazon are:

1.3.1 SRS Document - Software Requirement Specification Document:

First deliverable in a Software product development lifecycle is the Software Requirements development. We will include all the functional and non-functional requirements in the requirements document. This Document will provide critical information to the team members in development, quality assurance, operations and maintenance. This will help keep everyone on the same page.

1.3.2 Web Scraping:

Main driving force behind our end software product will be the Web Scraping Model, which will scrape and extract the reviews of our client's product dynamically whenever a new review is added to the product reviews section. We will use the most powerful web scraping libraries of python like selenium, beautifulSoup4 and Scrapy.

1.3.3 Sentiment Analysis Model:

By scraping the product reviews from amazon and labelling the reviews as (positive, negative, or neutral), we will be all set to train our main machine learning Sentiment Analysis Model based on the labelled data available on the internet. On the basis of the training data given to the model, our model will predict the overall product's reviews sentiments.

1.3.4 Development of application and Model Deployment in an Application:

The full and final deliverable of our product will be the full fledge graphical user interface designed and integrated with our trained machine learning model, which will be available for use by the professional Amazon product sellers. They will insert the URL of their Amazon product and our model will scrape the reviews and then the model will predict about the product sentiment and deliver a dashboard report to the seller, which will assist them to sell their product in the most efficient way on Amazon.

Figure 1: Key Milestones or Deliverables

1.3.5 Dashboard:

By using real-time scrapped reviews data from Amazon product review section, we analyze sentiments of reviews to decide the outcome in the form of beautifully designed dashboard showing percentage of positive, negative, or neutral reviews. We also observed the potential impact of reviews on selling trends. The RNN model is methodical in making prediction on the time-series data. Also, we will help the seller to improve the areas of the product which are not liked by the general audience that is buyer in our case.

1.3.6 Advice:

Our model will advise both the buyer and the seller of the product. For instance, if a product has many positive reviews, then our machine learning model will advise the buyer to purchase this product and will not recommend buyer to purchase the product if it has many negative reviews. On the other hand, from seller point of view, it will advise him/her to upgrade certain area of his/her service or product that needs certain improvements so that he/she can improve his/her sale and meet customer expectations.

CHAPTER 02: LITERATURE REVIEW

2.1 Literature Survey

The field of study that analyzes a person’s opinion, feelings, appraisals, sentiments, assessments, and emotions is sentiment analysis and opinion mining. These characteristics might be expressed on any platform such as reviews, tweets, and comments. These can be either on items, services, associations, people, occasions, issues, or points. This field addresses a huge issue space. Other similar terms to sentiment analysis (that lie under the same umbrella), for instance includes opinion analysis, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, and review mining. Nasukawa and Yi (2003) coined the term sentiment analysis, while Dave et al. coined the term opinion mining (2003) [1].

Essentially, people are supposed to be subjective and regularly one-sided with assumptions. At present times, sentiments in all spheres and area of human development have a significant influence on human society. As a result, sentiment analysis of opinions can be viewed as a necessary tool for examining the mood and predominant attitude of any sample group of people regarding a specific item, service, occasion, or point communicated in content structure and distributed via social media stages, blog entries, remarks, comments, web reviews, and so on. Thanks to the growth and widespread of internet and smartphones all around the world, uploading of opinions, comments, and reviews is done with ease even in the most remote areas of poor countries. The trial of scrutinizing all posts and reviews and integrating them into meaningful direction might be rather considerable, according to the perspective of mining on such data and opinionated text material. Sentiment Analysis was created with the goal of presenting a summary of opinions classified into positive, neutral, and negative reviews based on analyses of texts posted by users on various digital platforms on the internet [2] [3]. Sentiment analysis ranks as a significant tool in this field as an analytical way to distinct calculation and temperament of people towards events, issues, products, services, people and organizations [4].

Sentiment analysis is considered as a significant computational learning tool for human attitudes, views, and emotions to the extent that human feelings are stated in terms of any unit. A unit can be thought of as a representation of events, persons, or even topics. To obtain sentiment, sentiment analysis uses three terms namely, feature and object, opinion orientation and opinion holder. The primary components on which sentiment analysis is based are Natural Language Processing (NLP), computational algorithms, and text analyzers, which are used to automatically extract and classify sentiments from online reviews [4]. The work of sentiment analysis is difficult due to the numerous technical obstacles that may be present in the way. These difficulties can range from object recognition to opinion orientation classification via feature extraction. Machine learning algorithms, either supervised learning or unsupervised learning techniques, are commonly used to perform sentiment analysis. Neural Networks, Naïve Bayes, and Support Vector Machine design approaches are some of the examples of supervised learning techniques [5].

Even though sentiment analysis and opinion mining are frequently used interchangeably (due to their fundamentally similar defining roots and relevance in the real world of analyzing human opinion and attitudes), some researchers believe they are not nearly the same [6]. According to this group of researchers, while opinion mining extracts and then aids in the examination of human opinions on any issue, person, organization, product, facility, or service, sentiment analysis goes beyond just recognizing sentiments expressed in text form by analyzing text extracted. As a result, the aim of sentiment analysis, according to this group of researchers, is to detect opinions, separate and identify underlying sentiments, and then classify polarization of the opinions examined. When conducting sentiment analysis, it is common to assume that the data being analyzed will have clearly articulated opinions. In most cases, documents that are being studied include solely objective information. News items are an example. In some situations, things that are intended to contain sentiments or opinions can also include sentences that give facts and data. As a result, it becomes clear that the most significant characteristic of sentiment analysis is to first determine the kind and type of phrases in the text under consideration. While conducting a sentiment analysis, one of the most important tasks is to categorize statements in text as subjective or objective.

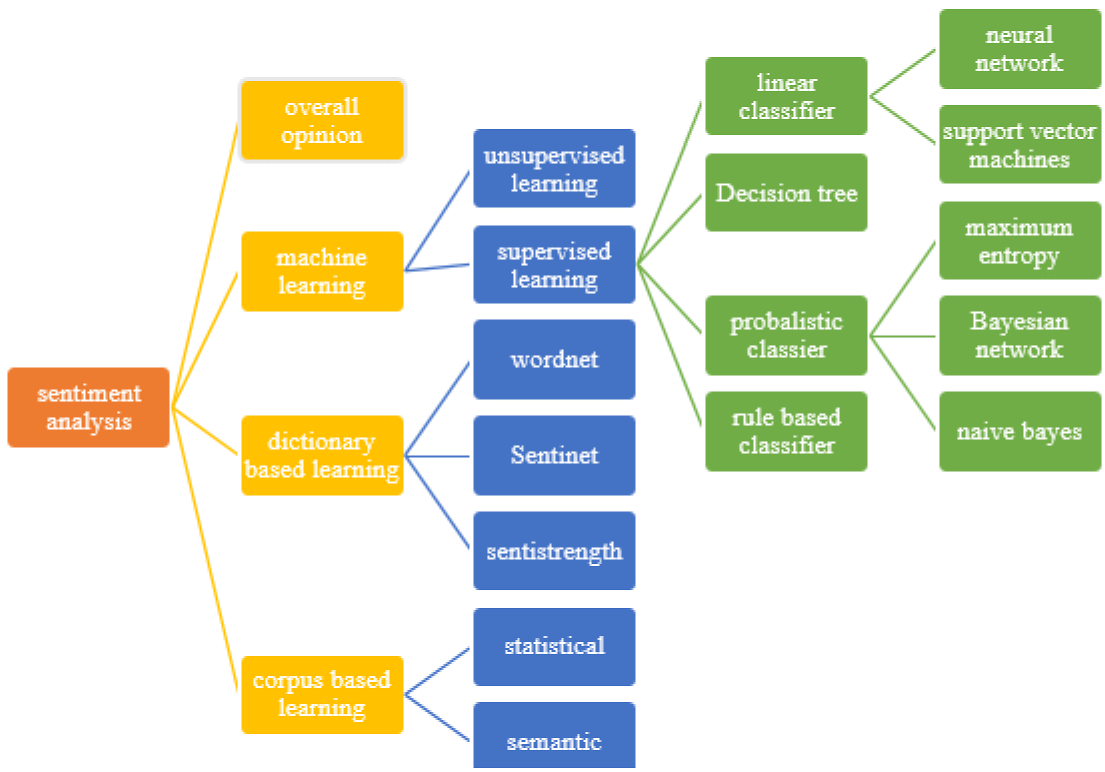


Figure 2 Sentiment classification techniques

The efficiency of current verbal resources and linguistic features for conducting sentiment analysis on Twitter tweets and similar microblogging posts was highlighted by Kouloumpis et al. [7]. In comparison to part-of-speech features and those pertaining to an existing sentiment lexicon, the researchers hypothesized that microblogging is more relevant and appropriate. Microblogging features are unlikely to supplement training data, according to the researchers. Another study [8] using rule-based classification and supervised learning methods discovered that hybrid classification was more related and produced capable outcomes. Since the turn of the century, sentiment analysis has been one of the most researched subjects in natural language processing [9, 10]. To streamline sentiment analysis methods, researchers have been continually evaluating sentences of various types. Mudinas et al. anticipated that a concept level sentiment analysis system (psenti) would be more effective than a lexicon-based approach [11]. According to their findings, the mix strategy is substantially more efficient and delivers more accurate results. Tripathy et al. developed four Machine Learning algorithms for sentiment classification in their study [12]. These were Naïve Bayes, Maximum Entropy, Stochastic Gradient Descent and Support Vector Machine. Their study showed that advanced classification can help reach accuracy. The researchers used the famous movie review website IMDB for their research. Using a mix of TF-IDF and count vectorizer techniques, the researchers were able to obtain excellent accuracy using an n-gram approach. To address the issue of punctuation marks and emojis that although accessible to humans, did not have a formal definition in the English language. The researchers created a new list of such words to assist sentiment analysis.

In another study that included e-commerce and online product reviews, the researchers [13] specified that public opinions and those of customers of products offered on online selling platforms would have broad relevance in terms of profitability, success, and productivity. As a result, companies and individuals invest in opinion mining and sentiment analysis to figure out how to stay ahead of the competition. The researchers use the FRBAS R package to build fuzzy rule-based systems (FRBS) with Mamdani and Takagi Sugeno Kang (TSK) models. The authors then compare these models to other classification strategies and rate them according to their f-measure, recall, precision, performance, and accuracy.

2.2 Market Survey

Innovation in the field of sentiment analysis is moving at a lightning pace, as it is in all aspects of machine learning applications in the real world. It has an extensive range of applications in the tech Industry. Sentiment analysis is already providing insights that help create effective company strategies, decisions, and objectives across a range of divisions as a very useful tool for social media companies, business owners, and advertising professionals. These perceptions might range from an assessment of a brand and its competitors to a comparison of a product's performance in potential international marketplaces. Sentiment analysis, on the other hand, is being employed in unexpected ways. The influence of these processes may be brought to bear on a variety of analytical activities, which could be a distinct advantage for advertisers. Sentiment analysis enables you to fine-tune a message for maximum impact, from the highest level of movement to the smallest phrasing on a landing page. This is something that the economic facilities sector is already looking into. By combining the ability of machine learning to analyze the sentiment of business statements and process analytical data in real-time, financial institutions such as Amazon, eBay, and Draz are increasingly able to rely on artificial intelligence to make the spontaneous decisions that drive the market. Whether we're trying to create long-term trends or we’re trying to figure out how to make a single piece of content to have a direct impact, sentiment analysis could help us out.

A market study is a methodical strategy that incorporates data collecting and analysis on any pertinent marketing-related concerns. Research is used in marketing for a variety of goals, including gathering customer perceptions, gauging customer satisfaction, determining the efficiency of advertising, and so on. While some larger companies have in-house market research divisions, smaller companies typically outsource the role to research specialists. Qualitative and quantitative research methodologies are the most common and widely employed. In a qualitative approach, the investigator makes knowledge claims primarily based on constructivist viewpoints (i.e., the multiple meanings of individual experiences, meanings socially and historically constructed, with the goal of developing a theory or pattern) or participatory viewpoints (i.e., political, issue-oriented, collaborative, or change-oriented) or both [14]. Finding out what individuals think and how they feel is a part of qualitative research. This type of information is ephemeral. Rather than numbers, it contains sentiments and impressions. Quantitative research, on the other hand, focuses on determining an objective fact. The definition of variables of interest and, to a significant extent, a sense of indifference in data gathering by the researcher are key components of quantitative research. The quantitative analysis investigates data using perceptions and relies on large examples to provide summed-up statements.

The link between quantitative and qualitative research has never been simple or straightforward. The logical validity of subjective inquiry in enhancing the development of logical ideas has sparked heated debate among researchers. Followers of qualitative research question the reliability of quantitative research, stating that the emphasis was solely on reinforcing and verifying existing models rather than generating new ideas. Despite the ongoing procedural discussion, a new trend in research has emerged today: mixed method research designs, also known as multiple research designs. Plural research design is a popular trend in social science research that integrates qualitative and quantitative research approaches in market studies. It regards qualitative and quantitative methodologies as only tools for understanding the world in which we live. Both tools are linked by shared responsibility for information generation, disseminating information, and conducting a comprehensive, honest analysis. Analysts are asked to make the majority a reality through triangulation, which combines both qualitative and quantitative approaches to data collection and planning.

An advertiser can use sentiment analysis to gain valuable insights into their clients' emotions, feedback, conclusions, and feelings over time. In comparison to traditional subjective statistical surveying approaches such as perceptions, meetings, interviews, and even ethnography, sentiment analysis provides a faster, less difficult, and more cheap solution. At the same time, it has the advantages of traditional quantitative techniques, such as quantifiability and objectivity. When compared to methodologies used in both qualitative and quantitative research, information is also acquired in a fully unobtrusive manner. Sentiment analysis allows advertisers to collect data on customers in their normal digital environment, without the presence of a scientist being sensed. As a result, this technique eliminates the problem of people reacting differently when they learn their responses are being recorded.

Table 1 Market Survey Table

Available Choices	Relevancy	Paid	Sentiment Analysis
Helium10	✗	✓	✗
Monkey Learn	✗	✓	✓
Brand24	✗	✓	✓
Sentiment124	✗	✓	✗
Our Model	✓	FREE	✓

CHAPTER 03: PROPOSED SOLUTION

We'll look at how deep learning approaches may be used to the task at hand. Sentiment Analysis is the process of determining if the passionate tone of a line, section, report, or any other piece of natural language is positive, negative, or neutral.

In this section we will experience various points like word vectors, recurrent neural networks, and Bidirectional Long Short-Term Memory (**BILSTM**). That we used in our project to reach our goal that is to classify sentences of the Amazon reviews.

3.1 Methodology:

PHASE - I

3.1.1 Download Labelled Dataset.

First, we must download a supervised data available on the internet, so that our learning can be supervised. There are numerous sources from where data can be gathered, for example kaggle.com, amazon dataset store and Stanford dataset library. While searching through the datasets, we came across a dataset of 1.6 GB that was not specifically directed towards one category of the products. Rather, it was a kind of universal type of data with more than 10 lac entries in train data and in the test data, it was almost nearly 05 lac. The link to the data is given as https://figshare.com/articles/dataset/Amazon_Review_Polarity/13232501/1 about this dataset following information was available on the internet.

DESCRIPTION of Data:

The polarity dataset for Amazon reviews is made up of review scores 1 and 2, with class 1 indicating a bad review and class 2 indicating a good review. The dataset excludes samples with a score of 3. A total of 1,800,000 training and 200,000 testing samples are available for each class. All training samples are stored as comma-separated values in the files train.csv and test.csv. They include three columns, one for each class index (1 or 2), one for the review title, and one for the review content. Double quotes (") are used to escape the review title and text, and two double quotes are used to escape any inside double quotations (""). A backslash is followed by a "n" character that is "\n" to create new lines.

3.1.2 Cleaning and feature extraction of the dataset

Cleaning the data is not a simple step. It requires time, effort, and energy. Also, some of the feature extraction techniques is also in this step, in our case is the vocabulary of words. Now that we have downloaded the data, our next step would be to clean the data in the most effective way. One way of doing so is listed below or we can say following is the path that we will consider while cleaning our data and feature extraction.

Things to remember while doing "**Feature Extraction and Cleaning**" are:

- **Handling stop words**
    - First download the stop words list from nltk or any other better source and update the stop words list.
    - Ignored as stop words are of no use in our model.

```
from nltk.corpus import stopwords
stop = stopwords.words('english')
df['Text'] = df['Text'].apply(lambda x: " ".join(x for x in x.split() if x not in stop))
```

- **Handling any of the missing values**
    - Often, these values discarded if found.

```
df= df.dropna()
df.shape
```

- **Make all text to lower case**
    - Just for convention

```
df['Text'] = df['Text'].apply(lambda x: " ".join(x.lower() for x in x.split()))
```

- **Removing Punctuations**
    - As punctuations are of no use to us, we will delete them

```
df['Text'] = df['Text'].str.replace('[^\w\s]','')
```

- **Removing URLs**
    - Any URLS in the document will be of no use to our model

```
def remove_url(text):
    url = re.compile(r'https?://\S+|www\.\S+')
    return url.sub(r'', text)
```

```
# remove all urls from df
import re
import string

df['Text'] = df['Text'].apply(lambda x: remove_url(x))
```

- **Remove any HTML tags**
    - People sometimes use html tags in their review so we have to remove them.

```
def remove_html(text):
    html=re.compile(r'<.*?>')
    return html.sub(r'',text)
```

```
# remove all html tags from df
df['Text'] = df['Text'].apply(lambda x: remove_html(x))
```

- **Removing Emojis**
    - This is the bread and butter these days. Review without emojis are hard to find so we have to remove these too.

```
def remove_emoji(text):
    emoji_pattern = re.compile("["
                           u"\U0001F600-\U0001F64F"  # emoticons
                           u"\U0001F300-\U0001F5FF"  # symbols & pictographs
                           u"\U0001F680-\U0001F6FF"  # transport & map symbols
                           u"\U0001F1E0-\U0001F1FF"  # flags
                           u"\U00002702-\U000027B0"
                           u"\U000024C2-\U0001F251"
                           "]+", flags=re.UNICODE)
    return emoji_pattern.sub(r'', text)
```

```
# remove all emojis from df
df['Text'] = df['Text'].apply(lambda x: remove_emoji(x))
```

- **Remove Emoticons**
    - Emoticons are like :) This also needs to be removed in the cleaning process of the data

```
from emot.emo_unicode import UNICODE_EMO, EMOTICONS

# Function for removing emoticons
def remove_emoticons(text):
    emoticon_pattern = re.compile(u'(' + u'|'.join(k for k in EMOTICONS) + u')')
    return emoticon_pattern.sub(r'', text)
```

```
df['Text'] = df['Text'].apply(lambda x: remove_emoticons(x))
```

- **Spell Correction**
    - Sometimes people do make mistakes that are typo errors so in order to cope up with this problem we have to provide a function to check spelling of the review so that it is nearly as good as possible for the model

```
from textblob import TextBlob
df['Text'][:5].apply(lambda x: str(TextBlob(x).correct()))
```

3.1.3 Transfer Learning (OR) Train a word vector model (Word Embedding)

A word embedding is employed, which is a mapping of words to a high-dimensional continuous vector space having comparable vector representations for various words with similar meanings.

To learn these distributed word representations, efficient methods exist, and it is usual for research groups to provide pre-trained models that have been trained on a large corpus of text documents under a permissive license.

So, there are two options available for the time being. One of the methods is to use pre trained embedding models available on the internet or use/build our own model to use it in our machine learning model. If we use a pre-trained Google word2vec embedding based on 3 million words and almost 300 dimensions to each word and it's around 3.6 GB in size or the GloVe pre-trained word2vec word embedding model build and trained by Stanford it has 2.2 million words and 300 dimensions. Other variants are also available but this one has the vast vocabulary and dimensions. They both developed their word embedding for their own use, but it can be reused for most of the natural language processing problems. This concept is also known as transfer learning, that is you made a model and you designed it in such a way that others can also use that.

- **Loading pre-trained word vectors such as Word2Vec by google/Stanford**

As discussed earlier, we can use both the pre-trained models, but we will use Google's word2vec model because as per internet research, we came to know that the google model is very well trained than any other model also it can be one of the best sources of transfer learning. This model is also robust and performs well on any of the natural language processing dataset.

- **Training a word vector generation model (such as Word2Vec)**

We will also train our own word embedding model. Our model will be based on word2vec knowledge and in it, we will use the skip-gram method. If we go into a little detail, skip-gram is the technique in which we choose one word to predict its surrounding words that would be used in our model.

3.1.4 Model Selection RNN:

The next step is the model selection. We have decided to use the "Recurrent Neural Network". Out of many models, RNN are supposed to be the one that can be used in providing us better prediction results. The fact that NLP data is temporal is one of its distinguishing features. The context of each word in a phrase is crucial. We make use of a recurrent neural network to account for this reliance.

The recurrent neural network structure is a little different from the traditional feedforward neural network. As one has might see in traditional neural networks and have a visualization of Input, Hidden units and Output nodes As seen under the diagram:

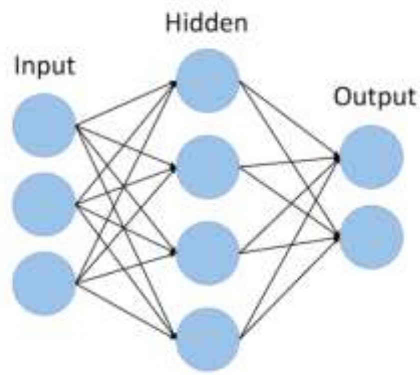


Figure 3 RNN model

The major distinction between feedforward and recurrent neural networks is the element of temporal. Each word in an input sequence is assigned to a distinct time step in RNNs this makes them unique from traditional RNNs. In effect, the maximum sequence length will be equal to the number of time steps.

A new component called a hidden state vector **ht** is associated with each time step. ht is a vector that summarizes information from earlier time steps, similar to how **xt** is a vector that captures all of the information of a given word. Xt is the context of the current word while ht is the summarized context of all the previous words.

The hidden state is calculated using both the current word vector and the hidden state vector from the previous time step. The sigma indicates that the combined activation of the two phrases will occur (Generally a sigmoid or tanh).

$$h_t = \sigma(W^H h_{t-1} + W^X x_t)$$

The 2 W terms in the above formulation represent weight matrices.

- W^X which we're going to multiply with our input word.
- W^H: **recurrent weight matrix** which is multiplied with the hidden state vector at the previous time step.
- W^H stays the same across all time steps.
- W^X vary for input to input.

The size of these weight matrices determines how much the current or prior hidden state affects the hidden state vector. The weight matrices are updated through an optimization process called backpropagation through time.

The hidden state vector at the final time step is fed into a sigmoid classifier where it is multiplied by another weight matrix outputs values between 0 and 1, effectively giving us the probabilities of positive and negative sentiment also for the mid values we have introduced another class that is neutral sentiment.

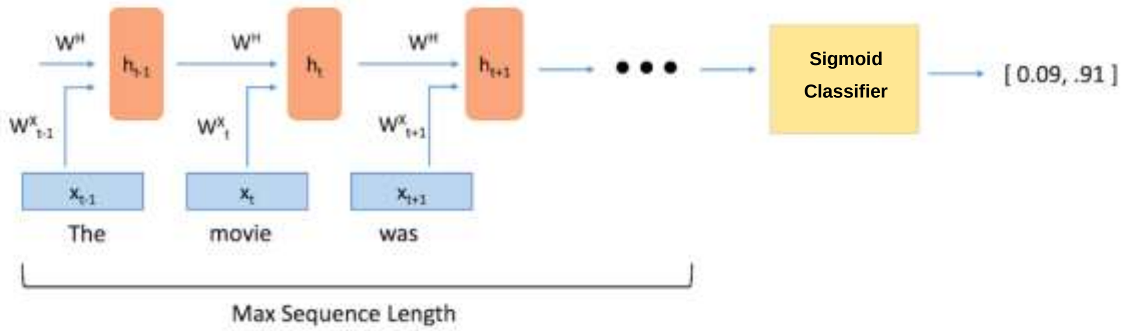


Figure 4 Sigmoid Binary Classifier

3.1.5 BILSTM cell

Sequence prediction problems are the hardest to solve in the artificial intelligence community. There are certain problems in predicting sentiment of people as this is ever changing and continuously changing regime. So, the data science community has got a breakthrough in the form of Long-Term Short Memory abbreviated as LTSM and BILSTM – Bidirectional Long Short-Term Memory (The updated version of LSTM) to analyze the sequence and time series data. It is the most efficient algorithm available right now, so we have used this algorithm to predict the stock faith for the companies.

> "Bidirectional recurrent neural networks link two hidden layers with opposing orientations to a single output. The output layer of this type of generative deep learning may collect knowledge from both past and future states at the same time."

Why use BILSTM?

Example:

Consider the following scenario:

Passage: "The first number is 3. The dog ran in the backyard. The second number is 4."

Question: "What is the sum of the 2 numbers?"

We can observe that the middle phrase had no bearing on the issue being posed. The first and third phrases, however, have a strong relationship. The hidden state vector at the conclusion of a traditional RNN may have saved more information about the dog sentence than the first sentence about the number. We have to use a better approach to capture this information, and for that we have Bilstm cell.

So, for very Long sentences and where one thing is relating to the thing that is at the end of the sentence, paragraph, or even a summary then we should have to capture the context of that. So, we have to use the knowledge of the future plus the current knowledge including knowledge of past to capture the context of the sentence. Generally, reviews are long and to cope up with that problem Bilstm is the one that can produce effective results.

Model:

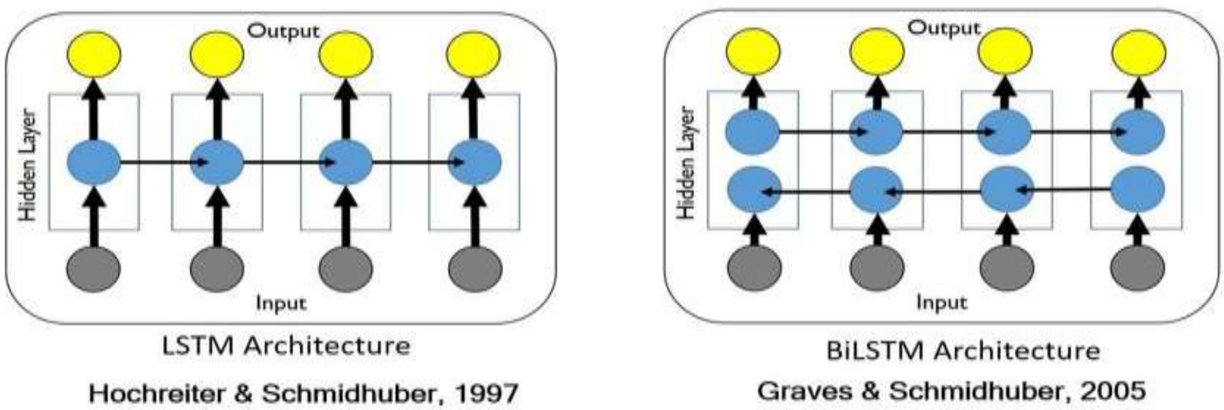


Figure 5 Bilstm cell

3.1.6 Hyper Parameter Training

Choosing the right values for our hyper parameters is a crucial part of training deep neural networks effectively.

- Learning Rate
- Optimizer
- Dropout
- Number of BILSTM units
- Embeddings dimensions

3.1.7 Train/Test split

After encoding the data, the data is ready to be induced into the algorithm to let it learn from the data, but the algorithm is always trained on the training set data and then tested through the test data. According to research, it is devised that data should be split as 80% for training and 20% for testing. Because model gets to learn from the training data and to check if the model has trained well, it is tested on the test data set.

3.1.9 Save Model.

Last step of this part is to save the model as model.py. This would contain code for the machine learning model to predict sentiments in the text/ csv file based on the parameters on which our original model is based.

PHASE - II

3.1.10 Web Scrapping

We have scraped the reviews data from Amazon.com. One will write a program that queries internet servers, requests, and retrieves information, parses it to extract information and store it in a csv file.

- Request
- Beautiful soap
- Selenium

Inspect the Amazon.com Website

Right click on the website to inspect the elements of the Amazon website in order to know what we want to scrape.

Parse HTML with Beautiful Soap Python Library

We have used beautiful soap for parsing the reviews from amazon website. Beautiful Soup is a Python bundle for parsing HTML and XML records (counting having contorted markup, for example non-shut labels, so named after label soup). It makes a parse tree for parsed 21 pages that can be utilized to extricate information from HTML, which is valuable for web scratching. By parsing html, we can get the tags of our choice.

3.1.11 Set the output Results where Reviews are found and were not found.

After the one has provided the input URL to the system then it is the made the duty of the system to check for if reviews do exist at the provided link or not. If the reviews are found, then we should direct the user to Dashboard screen an in other case to the Error page Screen.

PHASE - III

3.1.13 Let the input of saved model be the scrapped csv file.

The test file for the model or now or in other words in the real world or it is basically the deployment of the model into the real world so the scrapped data will be the input to the model and our model will classify the sentiments of each review and will save it to a csv file.

PHASE - IV

3.1.14 Dashboard creation using flask or Django:

Lastly, we have integrated our model into a web app, based on latest tools flask. We used Flask pipeline to integrate the model with our web app. On the user end runs the flask application and at the backend runs our trained sentiment analysis model.

3.2 Experimental/ Simulation Setup:

We used many tools and simulation setup. Some of the key Simulation setups are given below:

On our model plan, we're using the Python programming language, which is a well-known, high-level, and all-around useful programming language. With its clear usage of fundamental whitespace, Python's structural thinking emphasizes code consistency. Its language offers an object-oriented framework that aids programming engineers in creating clean, predictable code for low- and high-degree projects. Python is always being created, and garbage is constantly being assembled. It supports a variety of programming paradigms, including sorted (especially procedural), object organized, and viable programming.

NumPy is Python's primary library for scientific computing. It includes a high-performance multidimensional array object as well as utilities for manipulating them. NumPy is being used since we have a lot of numerical data and visualizations. Numpy is a Python package that includes support for gigantic, multi-dimensional bunches and structures, as well as a wide range of high-level logical abilities to attack these displays. NumPy combines the warring numarray's characteristics into Numeric, allowing for a wide range of changes. Numpy is an open-source programming language that has a wide range of supporters.

Pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language.

In computer programming, pandas is a data control and analysis library written for the Python programming language. It provides information structures and actions for regulating numerical tables and time scheduling, in particular. As we are dealing with time series analysis pandas is the best library to use

Colaboratory, or “Colab” for short, is a product from Google Research. Colab allows anybody to write and execute arbitrary python code through the browser, and is especially well suited to machine learning, data analysis and education. More technically, Colab is a hosted Jupyter notebook service that requires no setup to use, while providing free access to computing resources including GPUs.

We used Colab to train our model using their GPUs.

TensorFlow is a free and open-source software library for machine learning. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks. Tensorflow is a symbolic math library based on dataflow and differentiable programming.

TensorFlow is a free and open-source dataflow and differentiable programming library that may be used for a variety of purposes. It is a significant math library, and that is the reason why we are utilizing it in our neural system model.

Beautiful Soup is a Python package for parsing HTML and XML documents. It creates a parse tree for parsed pages that can be used to extract data from HTML, which is useful for web scraping.

We used beautiful soup as discussed earlier to scrap the reviews from amazon.com.

Flask is a micro web framework written in Python. It is classified as a micro framework because it does not require particular tools or libraries. It has no database abstraction layer, form validation, or any other components where pre-existing third-party libraries provide common functions.

We used flask to integrate our ML model to a web application.

Keras

Keras is a Python-based deep learning API that runs on top of TensorFlow, a machine learning platform. It absolutely was created with the goal of quick experimentation. It's crucial to be able to get from idea to outcome as quickly and feasible when conducting research.

Engineers and researchers may use Keras to completely use TensorFlow 2's scalability and cross-platform capabilities: you'll be able to run Keras on TPU or huge clusters of GPUs, and you'll be able to export Keras models to run within the browser or on a mobile device.

Experimental/ Simulation Setup - Diagram:

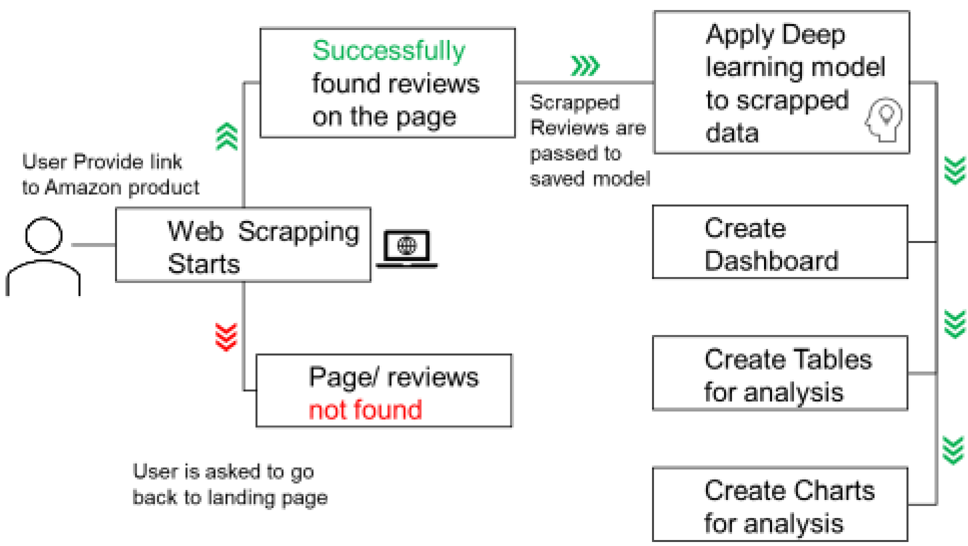
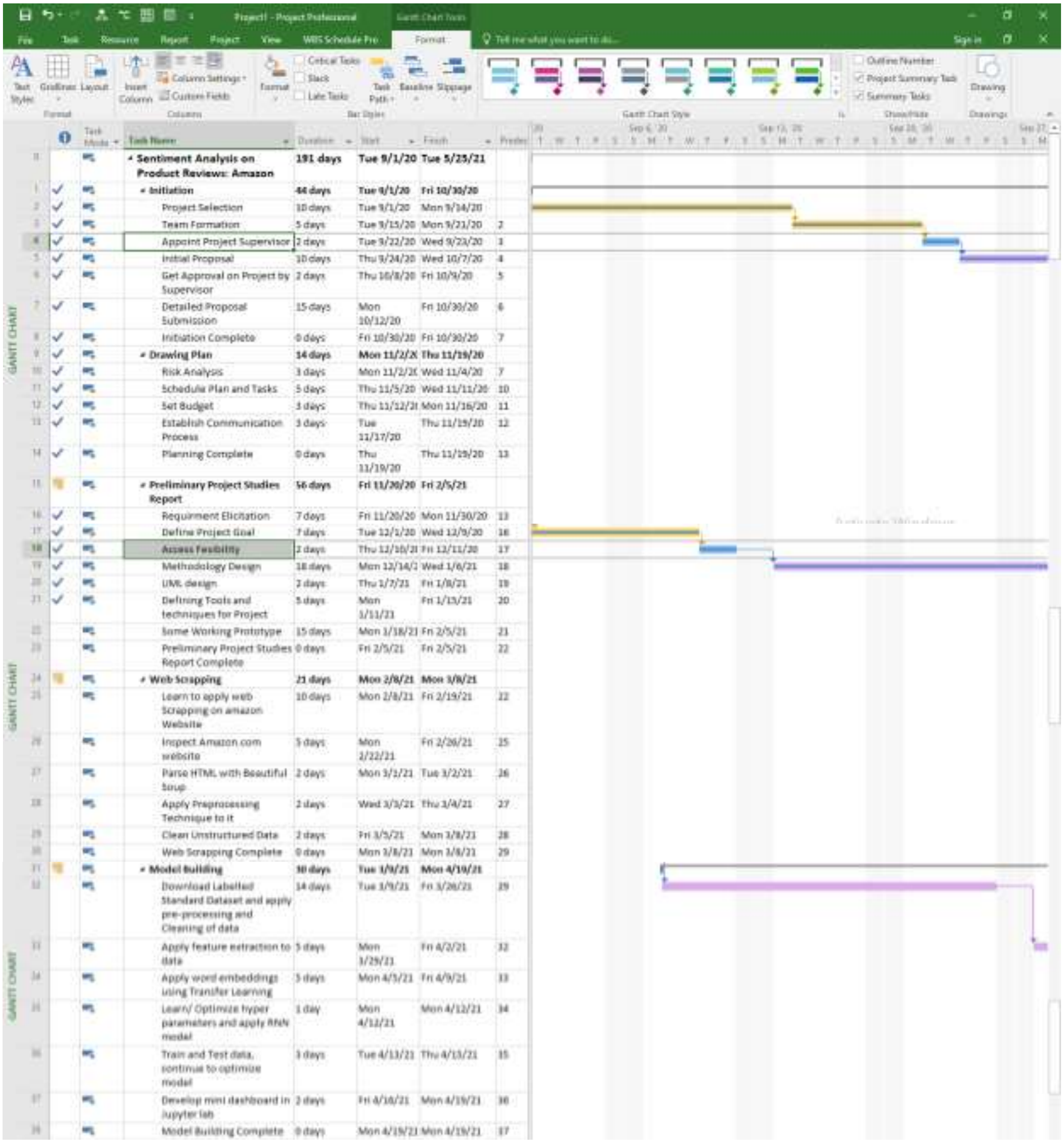


Figure 6 Simulation Setup Diagram

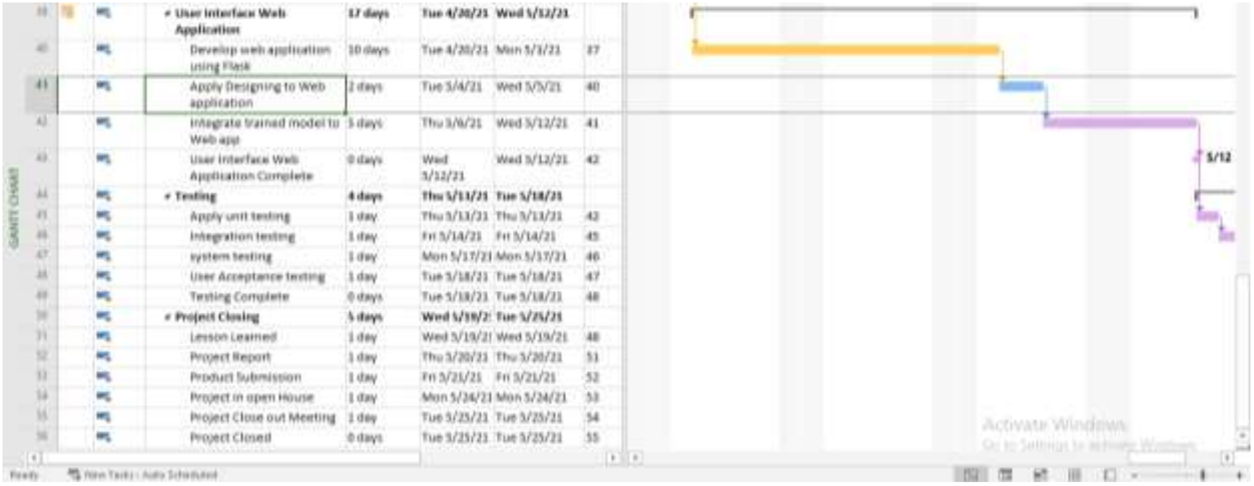
3.3 Project Timeline:

ID		Task Mode	Task Name	Duration	Start	Finish	Predecessors
1			Sentiment Analysis on Product Reviews:	191 days	Tue 9/1/20	Tue 5/25/21	
2			Initiation	44 days	Tue 9/1/20	Fri 10/30/20	
10			Drawing Plan	14 days	Mon 11/2/2	Thu 11/19/2	
16			Preliminary Project Studies Report	56 days	Fri 11/20/20	Fri 2/5/21	
25			Web Scrapping	21 days	Mon 2/8/21	Mon 3/8/21	
32			Model Building	30 days	Tue 3/9/21	Mon 4/19/2	
40			User Interface Web	17 days	Tue 4/20/21	Wed 5/12/21	
45			Testing	4 days	Thu 5/13/21	Tue 5/18/21	
51			Project Closing	5 days	Wed 5/19/2	Tue 5/25/21	

3.4 Details of Work packages completed/milestones achieved:



Task Name	Duration	Start	Finish	Predecessors
Sentiment Analysis on Product Reviews: Amazon	**191 days**	**Tue 9/1/20**	**Tue 5/25/21**	
Initiation	**44 days**	**Tue 9/1/20**	**Fri 10/30/20**	
Project Selection	10 days	Tue 9/1/20	Mon 9/14/20	
Team Formation	5 days	Tue 9/15/20	Mon 9/21/20	2
Appoint Project Supervisor	2 days	Tue 9/22/20	Wed 9/23/20	3
Initial Proposal	10 days	Thu 9/24/20	Wed 10/7/20	4
Get Approval on Project by Supervisor	2 days	Thu 10/8/20	Fri 10/9/20	5
Detailed Proposal Submission	15 days	Mon 10/12/20	Fri 10/30/20	6
Initiation Complete	0 days	Fri 10/30/20	Fri 10/30/20	7
Drawing Plan	**14 days**	**Mon 11/2/2**	**Thu 11/19/20**	
Risk Analysis	3 days	Mon 11/2/2	Wed 11/4/20	7
Schedule Plan and Tasks	5 days	Thu 11/5/20	Wed 11/11/20	10
Set Budget	3 days	Thu 11/12/2	Mon 11/16/20	11
Establish Communication Process	3 days	Tue 11/17/20	Thu 11/19/20	12
Planning Complete	0 days	Thu 11/19/20	Thu 11/19/20	13
Preliminary Project Studies Report	**56 days**	**Fri 11/20/20**	**Fri 2/5/21**	
Requirment Elicitation	7 days	Fri 11/20/20	Mon 11/30/20	13
Define Project Goal	7 days	Tue 12/1/20	Wed 12/9/20	16
Access Feasibility	2 days	Thu 12/10/2	Fri 12/11/20	17
Methodology Design	18 days	Mon 12/14/2	Wed 1/6/21	18
UML design	2 days	Thu 1/7/21	Fri 1/8/21	19
Defining Tools and techniques for Project	5 days	Mon 1/11/21	Fri 1/15/21	20
Some Working Prototype	15 days	Mon 1/18/21	Fri 2/5/21	21
Preliminary Project Studies Report Complete	0 days	Fri 2/5/21	Fri 2/5/21	22
Web Scrapping	**21 days**	**Mon 2/8/21**	**Mon 3/8/21**	
Learn to apply web Scrapping on amazon Website	10 days	Mon 2/8/21	Fri 2/19/21	22
Inspect Amazon.com website	5 days	Mon 2/22/21	Fri 2/26/21	25
Parse HTML with Beautiful Soup	2 days	Mon 3/1/21	Tue 3/2/21	26
Apply Preprocessing Technique to it	2 days	Wed 3/3/21	Thu 3/4/21	27
Clean Unstructured Data	2 days	Fri 3/5/21	Mon 3/8/21	28
Web Scrapping Complete	0 days	Mon 3/8/21	Mon 3/8/21	29
Model Building	**30 days**	**Tue 3/9/21**	**Mon 4/19/21**	
Download Labelled Standard Dataset and apply pre-processing and Cleaning of data	14 days	Tue 3/9/21	Fri 3/26/21	29
Apply feature extraction to data	5 days	Mon 3/29/21	Fri 4/2/21	32
Apply word embeddings using Transfer Learning	5 days	Mon 4/5/21	Fri 4/9/21	33
Learn/ Optimize hyper parameters and apply RNN model	1 day	Mon 4/12/21	Mon 4/12/21	34
Train and Test data, continue to optimize model	3 days	Tue 4/13/21	Thu 4/15/21	35
Develop mini dashboard in Jupyter lab	2 days	Fri 4/16/21	Mon 4/19/21	36
Model Building Complete	0 days	Mon 4/19/21	Mon 4/19/21	37



Task Name	Duration	Start	Finish	Predecessors
User Interface Web Application	**17 days**	**Tue 4/20/21**	**Wed 5/12/21**	
Develop web application using Flask	10 days	Tue 4/20/21	Mon 5/3/21	37
Apply Designing to Web application	2 days	Tue 5/4/21	Wed 5/5/21	40
Integrate trained model to Web app	5 days	Thu 5/6/21	Wed 5/12/21	41
User Interface Web Application Complete	0 days	Wed 5/12/21	Wed 5/12/21	42
Testing	**4 days**	**Thu 5/13/21**	**Tue 5/18/21**	
Apply unit testing	1 day	Thu 5/13/21	Thu 5/13/21	42
Integration testing	1 day	Fri 5/14/21	Fri 5/14/21	45
system testing	1 day	Mon 5/17/21	Mon 5/17/21	46
User Acceptance testing	1 day	Tue 5/18/21	Tue 5/18/21	47
Testing Complete	0 days	Tue 5/18/21	Tue 5/18/21	48
Project Closing	**5 days**	**Wed 5/19/2:**	**Tue 5/25/21**	
Lesson Learned	1 day	Wed 5/19/21	Wed 5/19/21	48
Project Report	1 day	Thu 5/20/21	Thu 5/20/21	51
Product Submission	1 day	Fri 5/21/21	Fri 5/21/21	52
Project in open House	1 day	Mon 5/24/21	Mon 5/24/21	53
Project Close out Meeting	1 day	Tue 5/25/21	Tue 5/25/21	54
Project Closed	0 days	Tue 5/25/21	Tue 5/25/21	55

3.5 Evaluation Parameters:

Scope:

Project Objectives	**Success Criteria**
Implement a machine learning algorithm to perform sentiment analysis accurately up to 0.80-0.90	0.85 ± 0.05
Understand and implement 95% natural language processing techniques.	95.0 ± 05%
Achieve 0.80 or more in training accuracy.	0.80 ± 0.05%
Build a 100% working web application graphical user interface for visualization purposes.	100%
Scrapped data validity must be 90%	90 ± 5%

Time:

Project will be complete in 22 weeks.	22 ± 06 (days)

Cost:

PKR Rs. 65,000 /-	65,000 ± 5000

Other:

End User satisfaction with the product review should be 4 as acceptable.	04 ± 01

Table 2 Evaluation parameter table

3.6 UML Diagrams:

3.6.1 Use Case Diagram

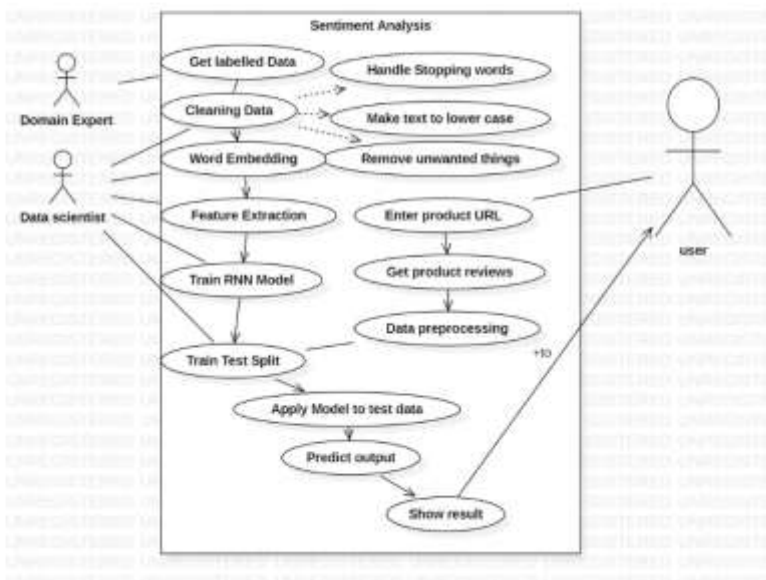


Figure 7 Use Case Diagram

3.6.2 Flow Diagram First Phase:

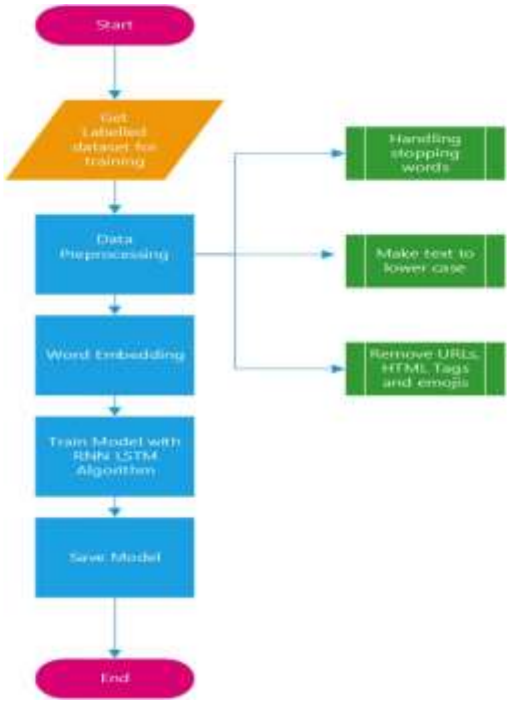


Figure 8 First Phase Flow Diagram

3.6.3 Flow Diagram Second Phase:

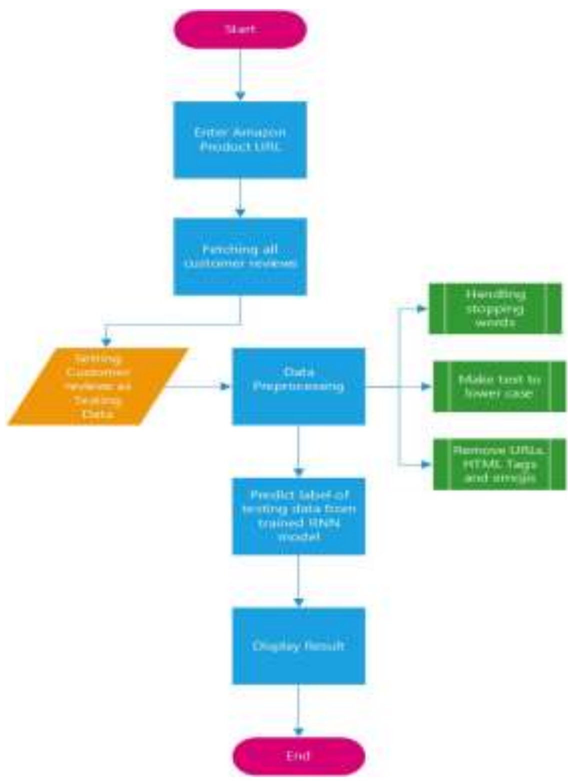


Figure 9 Second Phase Flow Diagram

3.6.4 Sentiment Analysis Overall block Diagram:

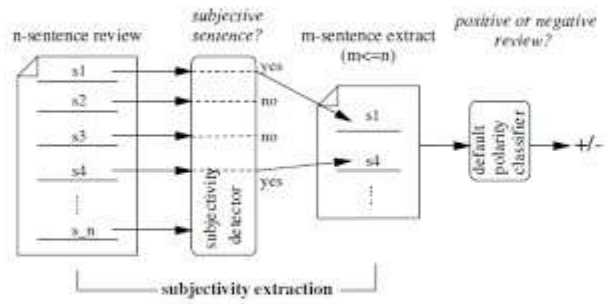


Figure 10 Block Diagram for sentiment analysis.

Chapter 04: Results and Discussion

4.1 Utilization (End Users/Beneficiaries):

Anyone can use our Web app from our official website with a single click and start using it right away. Initially, without needing to sign up for it but later on, some of the features will need registration of user and paid premium features will also be added to make our web app economically stable. The end users of our proposed project are as follows:

- Product Sellers
- Product Buyers
- To some potential, Amazon

4.2 Low Fidelity Prototype:

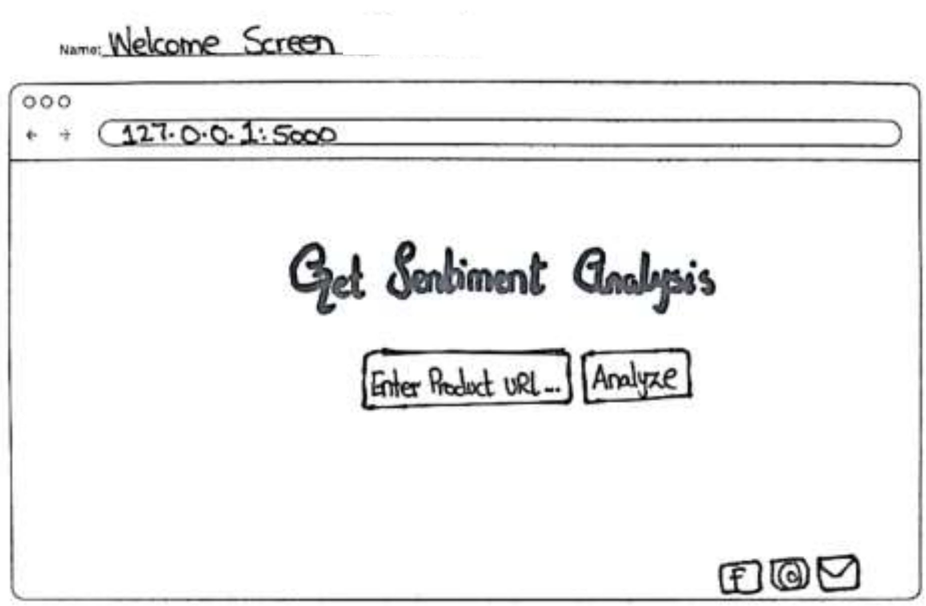


Figure 11 Low Fidelity - Welcome Screen

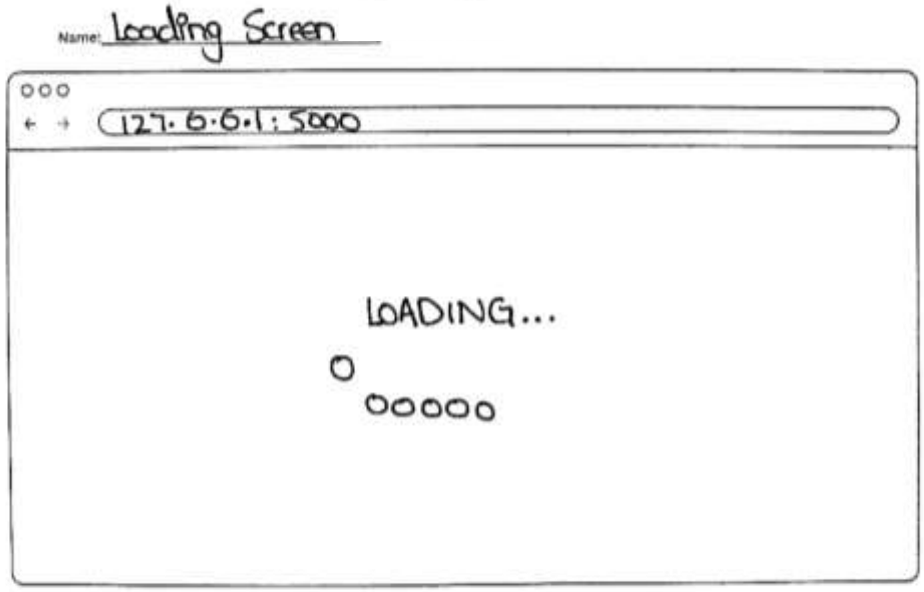


Figure 12 Low Fidelity - Loading Screen

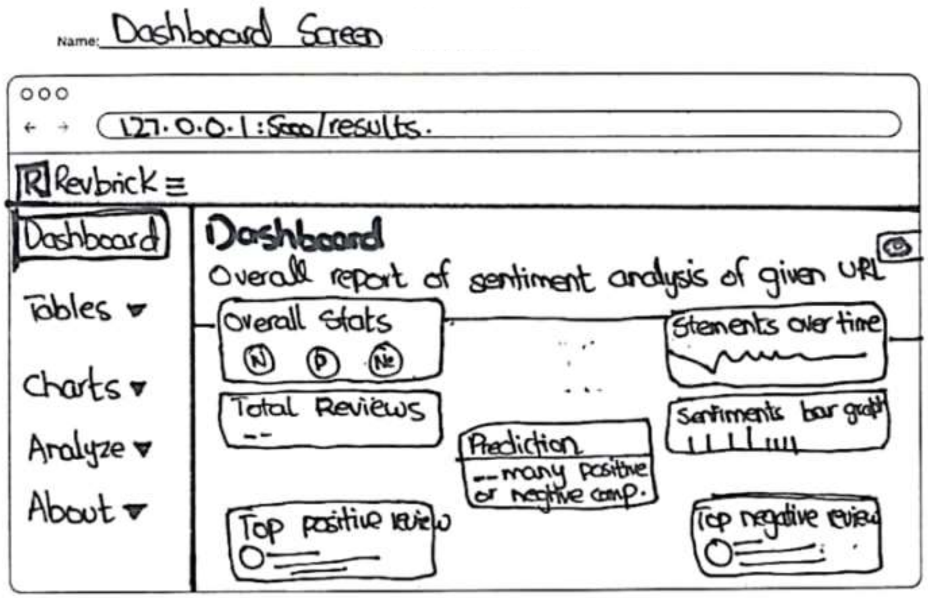


Figure 13 Low Fidelity - Dashboard Screen

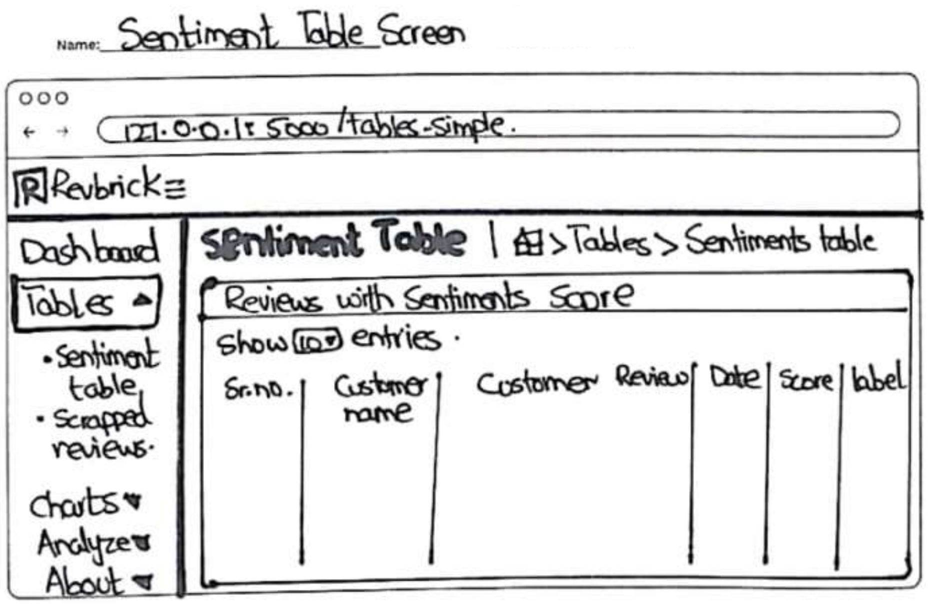


Figure 14 Low Fidelity - Sentiment table Screen

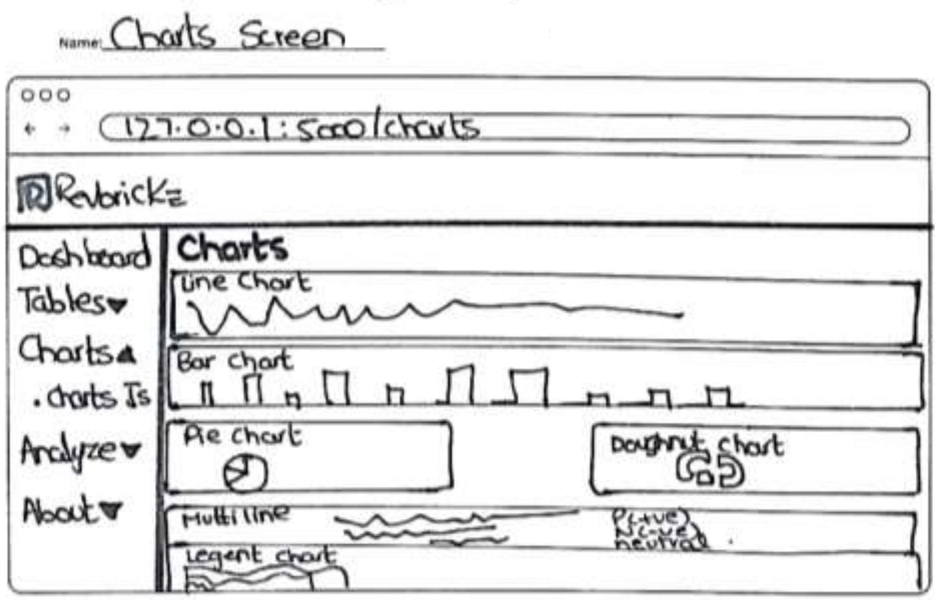


Figure 15 Low Fidelity - Charts Screen

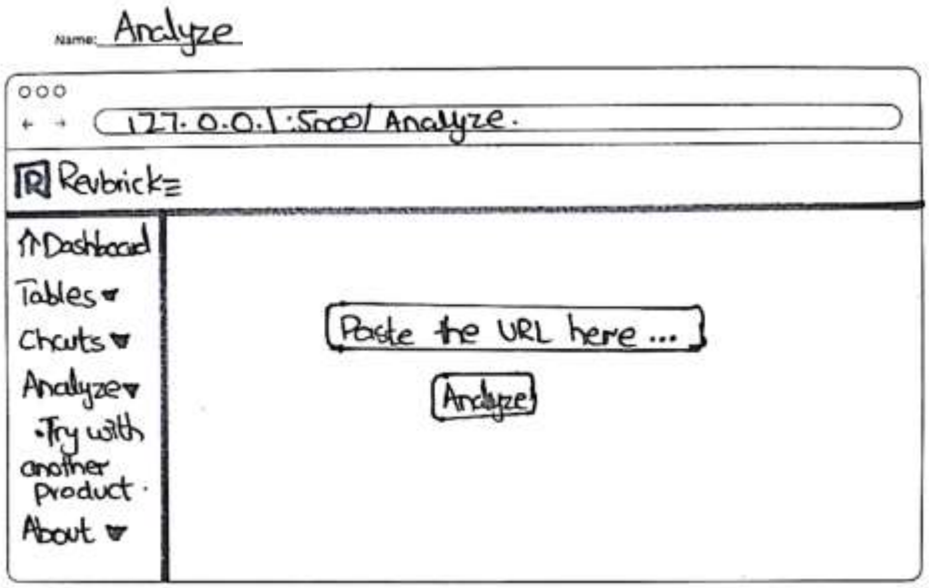


Figure 16 Low Fidelity - Analyze Screen

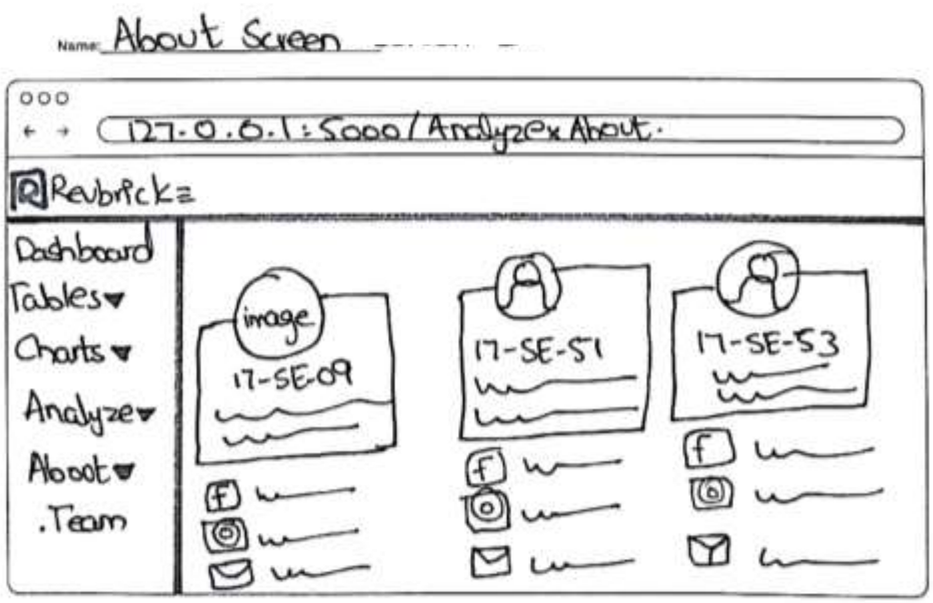


Figure 17 Low Fidelity - About Us Screen

4.2 Product Demo – High fidelity:

4.2.1 Homepage:

In this homepage or the landing page, user can only give full link of any amazon product then the *Analyze* button will enable. The link provided is validated and if the URL is correct or the format is correct then the user is able to click on the button analyze. Then after that our selenium driver will fetch that page and find the reviews on that page if reviews exist then after loading page the user of the web app will be directed to the dashboard page.

Figure 18 Homepage

4.2.2 Error Page:

If the given link of the product has no reviews or the given link is not of amazon product then this error page will be displayed.

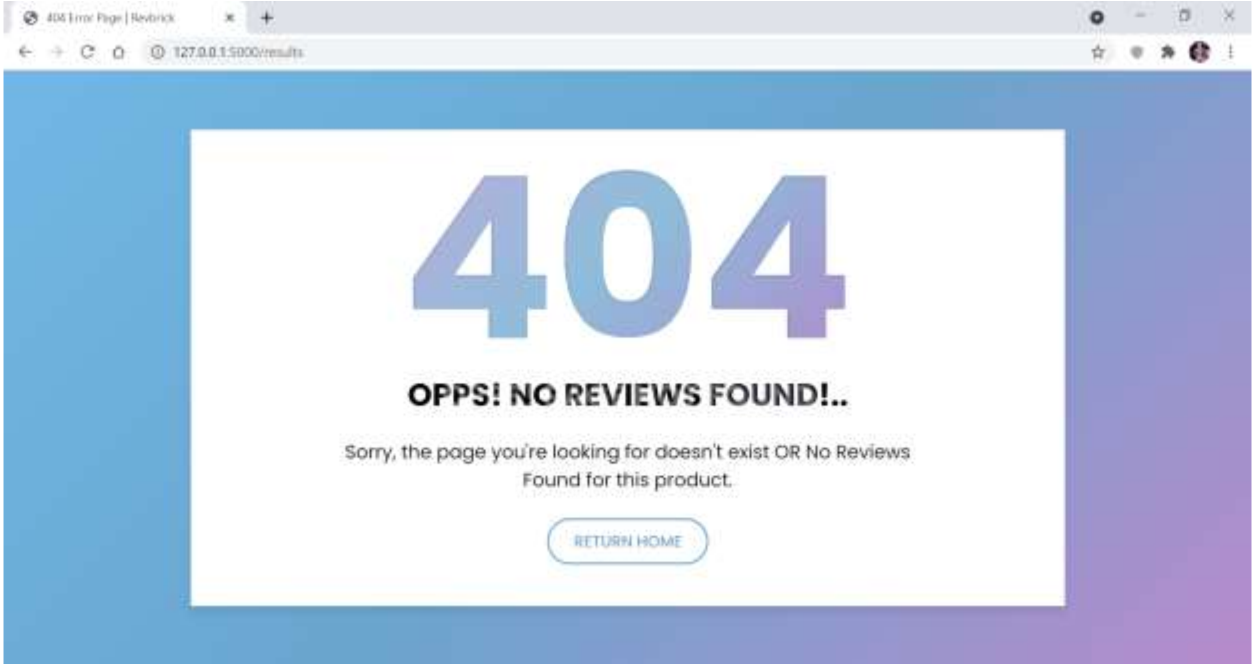


Figure 19 Error page

4.2.3 Waiting Page:

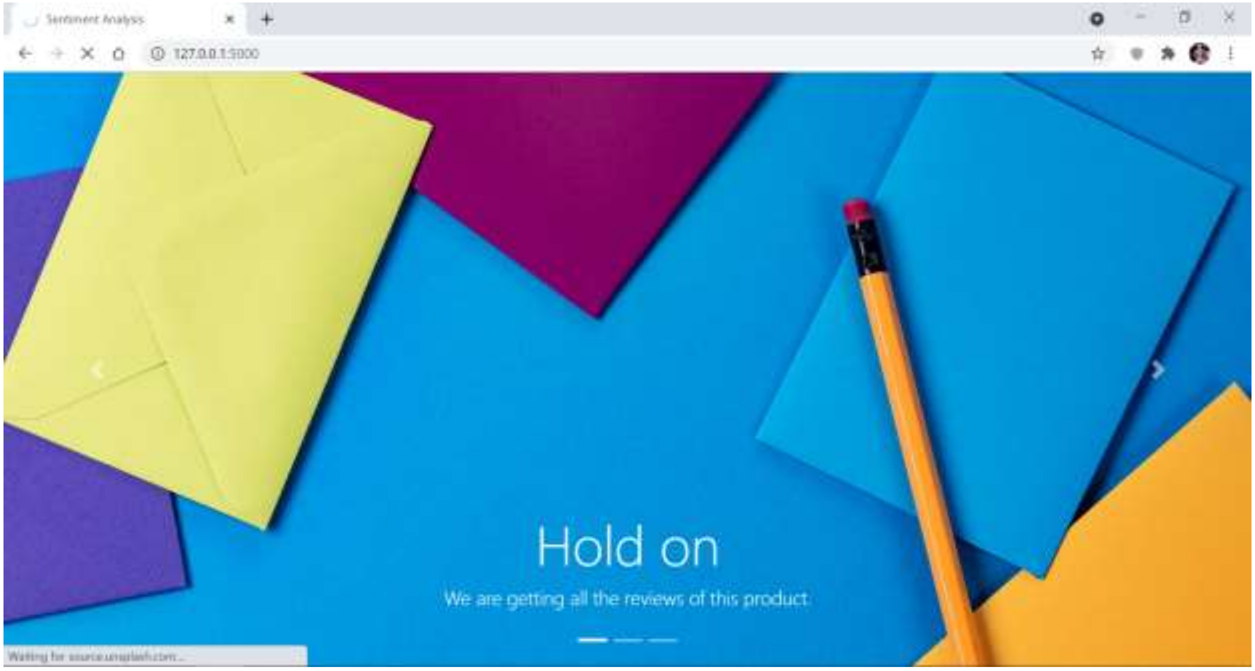


Figure 20 Waiting Page

This page will be shown while the reviews of given product link will scrapped and it will take some time to scrap the reviews and applying model on it.

4.2.4 Dashboard:

This is our web app's dashboard. On the first card, we have a total number of neutral, positive, and negative reviews that our model has classified. Then we have two types of graphs that are simply give the general overview of the product the complete reviews scores are limited on those graphs. Then we have a card of a total number of reviews. We also have a top positive and most negative review with the other details like customer name and date on our dashboard.

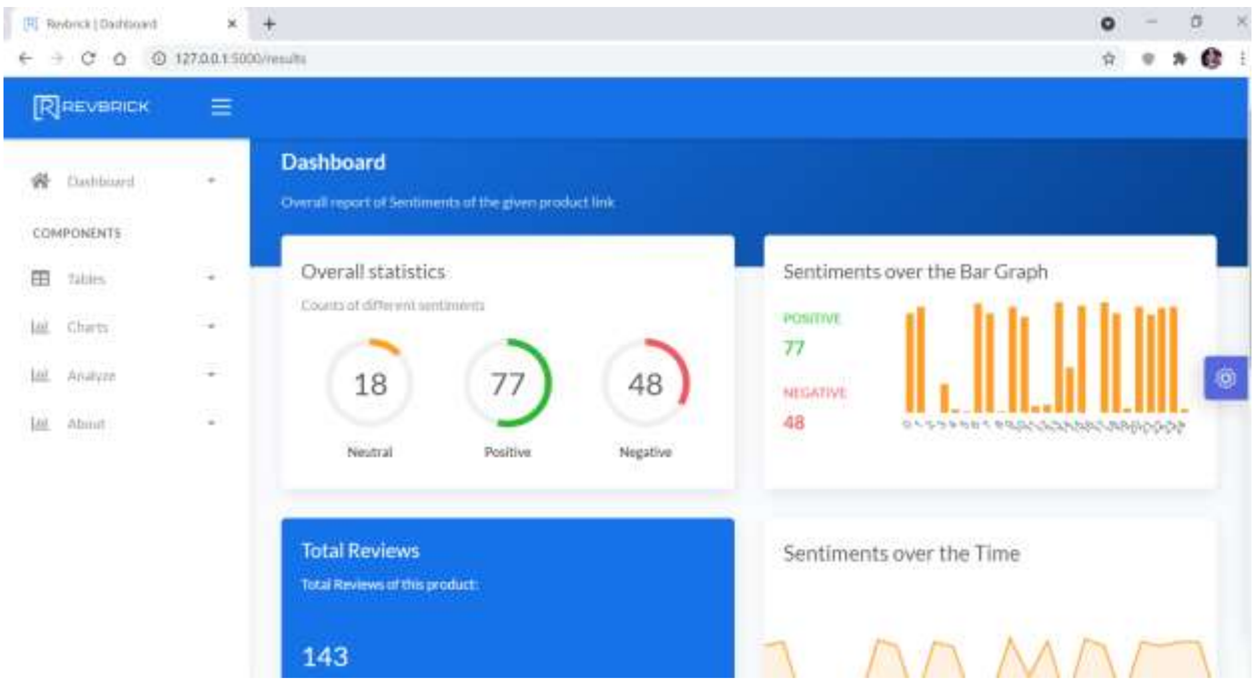


Figure 21 Dashboard

4.2.5 Detailed Charts:

On this page of our web app, we have a detailed overview of every sentiment. Here we have different charts that are showing analysis on reviews. Different types of charts with different comparisons are used to give a complete and best overview to the user. The pie chart with percentage information while doughnut chart with a total number of sentiments as classified in neutral, positive, and negative are used. This will give users different analyses that will increase the usability of our application.

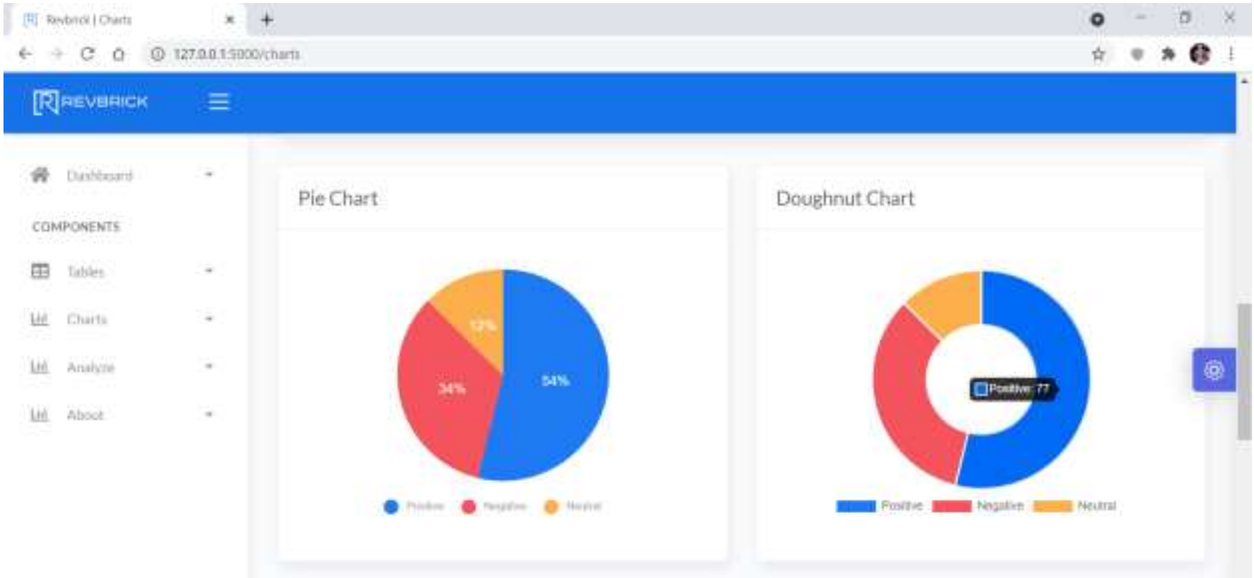


Figure 22 pie and doughnut Charts

Figure 23 Multiple Line Chart

This is multiline chart that give analysis of different classes on a single chart. So, the user can have complete analysis of data through visualization. Red graph is for negative while green is used for positive so it will give natural visualization and analysis to compare reviews. On vertical axis we have sentiment score of reviews and on horizontal axis we have number of reviews.

4.2.6 Sentiment Table with score:

This page contains all the scrapped reviews of the given product with their date, sentiment score, predicted label a positive, negative, or neutral, and also with customer name who posted that review. It will give complete information about the reviews of the product that can further be useful for the seller and buyer of that product. From this, we can also verify our working of the model by reading the comment and then verify its predicted label that our model classified.

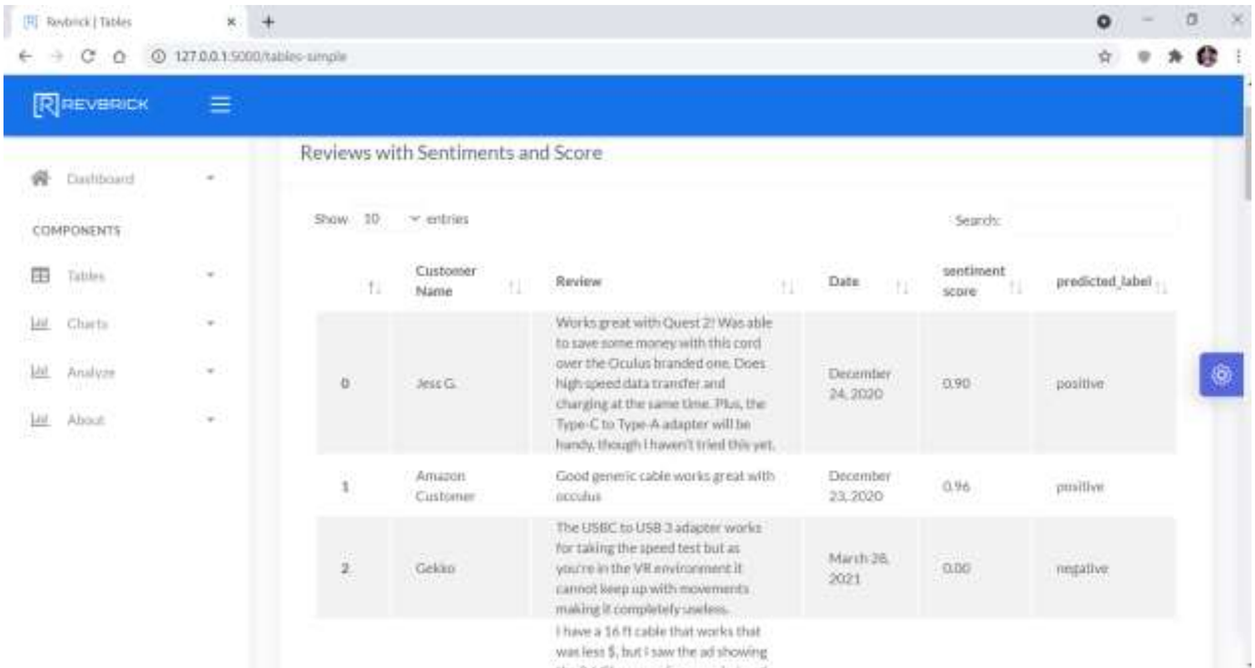


Figure 24 Table with sentiment score.

4.2.7 About Us Page:

This page consists of our team members' profiles.

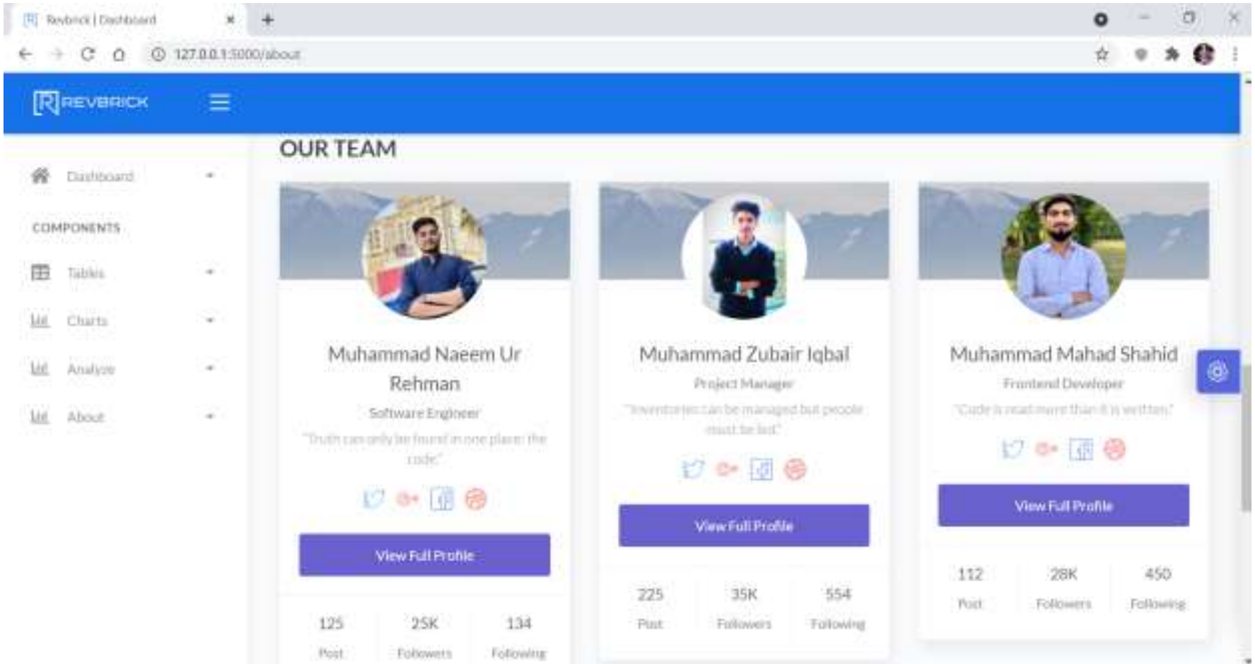


Figure 25 About Us page

4.3 Result Discussion:

We have developed one click-based user-interface which is highly attractive and easy to use. We have also made sure the software quality attributes that all the errors and exceptions are handling within the project. We have also kept in mind the seller as well as customer point of view for creating the design and different types of charts and detailed tables with scores are given so that user can have eagle-eye view within the product. User can also verify our prediction model while reading the comment and the score. We have trained our model on almost 1.5 million labelled data and we have achieved 90%+ accuracy with our prediction model.

Table 3 Compare Different Models

Model Used	Test Score
RNN+LSTM	57%
Bayes' Theorem	76%
Logistic Regression	83%
CON1D	87.6%
BERT	87.8%
RNN+Bilstm	90.14%

4.4 Budget Used:

This project used at least $570, and the budget sheet is shown in the table given below:

Table 4 Budget Plan table For Online Computing

System Requirements (if online)	Costs ($)
Google Co-Lab Services	$120 – 12 months subs
Website domain + Hosting	$200 - 6 months
Digital Marketing	$250 – 6months campaign

This project used at least $692, and the budget sheet is shown in the table given below:

Table 5 Budget Plan table - For offline Computing

System Requirements (if offline)	Costs ($)
512 GB SSD	$95
Processor - Intel core i7 8^{th} gen	$282
DDR4 – 16 GB RAM	$65
Digital Marketing	$250 – 6months campaign

*Assuming 1 Dollar= 159.72 Pakistani Rupees as per Monday 07-07-2021

We used offline budget for this project as we were having a laptop resource that was having capabilities equal to the mentioned table or a little less. Adding to this we run our application on the local laptop server and Marketing was not done due to lack of funds but we have planned a marketing strategy mentioned as below under the market forecasting heading.

4.5 Market Forecasting:

- Our Web app will improve the user experience and conversion rate of the Amazon sellers and will assist the buyers as well. We will work on the weaknesses of direct or indirect competitors of our niche in market, which will help us grow as a company.
- According to historical data, a product no matter how well developed, takes on average at least 4-5 years to build a solid customer base. This means we would be required to make continuous ads and publish them on popular social media platforms just to attract the customer side of the End Users.
- We target ecommerce market analysts to find out the product quality trends that are highly dependent on many relevant reviews from around the internet, which in our case is domain specific Amazon. Given the assumptions, we would develop a system capable of modeling the sentiment in response to squeeze reviews in Amazon review section of a product. In doing so, the sellers would have the option to foresee the future conduct of their product when relevant and valid reviews are being posted and will act immediately on it and we will promote it by using social media.
- As our web app is based on providing utility to e-commerce businesses, ads related to e-commerce are mostly seen on the social media. So, we will be using the same strategy, as our end user searches for these services most of the time on internet. This approach will provide us with the biggest audience to reach our goal.
- In this Digital era, it is easy to reach out the targeted audience in quick span of time. So, we are going to use digital marketing as our main tool to reach out to our Web application users.

4.4.1 Brief Description of marketing Plan:

4.4.1.1 Facebook Adverts:

As the minimum budget on Facebook Adverts is $1/ad. If we spend Rs.1000/ad, after running 3 ads the budget will be Rs.3000/week & Rs.12000/month through which not only we get our targeted potential audience but also impressions up to 100,000.

4.4.1.2 Google Adverts:

As the minimum budget on Google Adverts is $5/ad. If we spend Rs.2000/ad, after running 3 ads the budget will be Rs.6000/week & Rs.24000/month through which not only we get our targeted potential audience but also impressions up to 100,000.

Chapter 05: CONCLUSION

In this project, we used the latest deep learning approach to solve the problem of sentiment analysis. We looked at the various and challenging components of the entire process before moving on to the process of developing code to put the model into effect. Finally, we trained our model using the Bilstm cell with an accuracy of around 90% and tested the model so that it is able to classify amazon products reviews with a test accuracy of 90.14% and point to be noted is that our model is trained on 1.5 million reviews.

With the help of modern tools, technology, and techniques, we were able to create our own sentiment classifiers and we named it “Revbrick” to understand the large amounts of natural language sentiments underlying the reviews section of Amazon Products and use the results to form actionable insights and these actions are from both the ends the Product seller end and the Product buyer end as 91% of the people surf through the internet and read the reviews about the product they are about to buy so that they may make their mind in this way our website would play a key factor for them instead of reading all the reviews and classifying the in their minds that either they are positive or not they use our model to find general sentiments of the products with little or no effort also for the Product owner instead of paying to the big companies to watch over there product they are just a single click away to find what their customers are feeling about their product.

With little changes in our code, we can also expand our solution to different e-commerce websites like www.daraz.pk and www.ebay.com based on this model. In future, we have motivated to expand and advertise it on bigger market level.

CHAPTER 06: REFERENCES

1. BING LIU University of Illinois at Chicago 2015, “Sentiment Analysis Mining Opinions, Sentiments, and Emotions”.
2. S. ChandraKala, and C. Sindhu, “Opinion mining and sentiment classification: A survey”, ICTACT journal on soft computing, vol. 3, No. 1, pp. 420-425, October 2012.
3. B. Pang, and L. Lee, “Opinion mining and sentiment analysis, Foundations and Trends® in Information Retrieval”, Vol. 2, No. (1–2), pp. 1-135, July 2008.
4. E. Aydoğan, and M.A. Akcayol, “A comprehensive survey for sentiment analysis tasks using machine learning techniques, In Proceedings of 2016 International Symposium on Innovations in Intelligent Systems and Applications (INISTA)”, Sinaia, Romania, pp. 1-7, August 2016.
5. B. Agarwal, N. Mittal, P. Bansal, and S. Garg, “Sentiment analysis using common-sense and context information”, Computational intelligence and neuroscience, Vol. 2015, March 2015.
6. M. Tsytsarau, and T. Palpanas, “Survey on mining subjective data on the web”, Data Mining and Knowledge Discovery, Vol. 24, No. 3, pp. 478-514, May 2012.
7. Kouloumpis, T. Wilson, and J. Moore, “Twitter sentiment analysis: The good the bad and the omg!”, In Proceedings of the Fifth International AAAI conference on weblogs and social media, Barcelona, Catalonia, Spain, pp. 538-541, July 2011.
8. R. Prabowo, and M. Thelwall, “Sentiment analysis: A combined approach”, Journal of Informetrics, Vol. 3, No. 2, pp. 143-157, 2009.
9. B. Liu, “Sentiment analysis: Mining opinions, sentiments, and emotions”, Cambridge University Press, June 2015.
10. K. Ravi, and V. Ravi, “A survey on opinion mining and sentiment analysis: tasks, approaches and applications”, Knowledge-Based Systems, ELSEVIER, Vol. 89, pp. 14-4, November 2015.
11. Mudinas, D. Zhang, and M. Levene, “Combining lexicon and learning based approaches for conceptlevel sentiment analysis”, In Proceedings of the first international workshop on issues of sentiment discovery and opinion mining, Beijing China, pp. 1-8, August 2012.

12. L. Qu, G. Ifrim, and G. Weikum, , “The bag-of opinions method for review rating prediction from sparse text patterns”, In Proceedings of the 23rd international conference on computational linguistics, Coling 2010, Beijing ,Association for Computational Linguistics, pp. 913-921, August 2010.
13. S.M. Basha, Y. Zhenning, D.S. Rajput, N. Iyengar, and D.R. Caytiles, “Weighted fuzzy rule-based sentiment prediction analysis on tweets”, International Journal of Grid and Distributed Computing, Vol. 10, No. 6, pp. 41-54, June 2017.
14. Creswell, John. (2007). Qualitative Inquiry and Research Design. Choosing Among Five Approaches. 2nd ed. Sage Publications Inc: California.
15. Amazon Review Polarity Dataset, origin description and history https://figshare.com/articles/dataset/Amazon_Review_Polarity/13232501/1
16. Amazon reviews NLP capstone project by EnesGokceDS, dated: Sep 16,2020 link https://github.com/EnesGokceDS/Amazon_Reviews_NLP_Capstone_Project
17. Perform sentiment analysis with LSTMs, using TensorFlow by Adit Deshpande. Dated: July 13, 2017 https://www.oreilly.com/content/perform-sentiment-analysis-with-lstms-using-tensorflow/