Review Based Analysis of Mobile Phones

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Asjid Ahmed
Muhammad Suleman

Abstract

Review Based Analysis plays a vital role in mobile selection. Many techniques exist for the analysis of mobile phones. But feature-based analysis and fake reviews detection require understanding the context and meaning of the words. Two reviews conveying the same message can be written quite differently. The review analysis requires human intelligence and effort. We proposed an automatic review analyzer application that analyzes and gives the top suggestions. The system based on artificial intelligence verifies the reviews and allocates ratings accordingly. In the end, the evaluation proves that our approach gives much realistic behavior and can be used by the buyers and sellers.

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Chapter 1

Preliminaries and Introduction

Mobile phones have been one of the essential components for us during the last decades. The fact about human psychology is that our beliefs are highly motivated and influenced by the thinking and evaluation of other people. When the consumer wants to buy a specific product like a mobile phone, they will review a similar product and then or will read reviews. However, the studies may not always be truthfully provided, and fake reviews generally exit. More than 80% of the generated data are in text format [3]. Analyzing these problems and working on different techniques helped us develop a web application that provides sentiment analysis using machine learning algorithms to help get rid of the problem of selecting a mobile phone. It is predicted that sometime shortly, machine intelligence will surpass human intelligence, so by automating the review-based analysis; we can get the best results in the future [22]

1.1 Motivation

Users visit E-Commerce sites to shop for products and the opinion of other buyers and users of products. Customer reviews are helping consumers to decide which products are good to buy and also manufacturing companies to understand the buying behavior of consumers, qualities and defects of their products. [18].So We developed a web application that provides the best mobile phone suggestions based on selected features. It will save time by automating the analysis of reviews.

1.2 Objective

The objective is to develop a platform for the selection of mobile phones. To achieve that goal, the primary objectives should be fulfilled.

- Polarity of reviews.
- Training model on real data.
- Specific features selection.
- Analysis of the specific features of the mobile phone specifications.
- Analyzing the reviews based on the specific features.
- Detection and removal of fake reviews on opinions.

1.3 Scope:

We are providing the way of selecting mobile phones and analysis based on reviews ranking. Our analysis will be on some particular features.

1.4 Limitations:

- Works only on selective features.
- Computationally expensive.
- Accuracy may vary according to data-set.
- Can't reach human accuracy [2].

Chapter 2

Review of Literature

2.1 Techniques

The most important thing to choose was the proper technique on which we would train our model. After analyzing the literature, we came up with the following methods used in the review-based analysis.

- KNN
- Naive Bayes
- SVM
- BagOfWords
- Word2Vec
- LDA
- TextBlob

2.1.1 KNN

KNN [20] is widely used because it's simple to understand and easy to implement, but as the data set grows, the efficiency and speed of the model are highly decreased.

The features must be homogeneous, and it cannot deal with outliers.

2.1.2 Naive Bayes

Naive Bayes is used to finding each review's polarity, and it works well for high-dimensional data such as text classification. Independent features make Naive Bayes faster and perform better than other classifiers in terms of accuracy [21].

2.1.3 SVM(Support Vector Machine)

SVM [12] is mainly used for text classification. In the algorithm, each data will be plotted as a point in n-dimensional space with the value of each feature, n is the number of features.

2.1.4 BagOfWords

A most popular model which is widely used for sentiment analysis in NLP(Natural Language Processing) [6]. It is used for document classification where the frequency of occurrence of each word is considered as a feature for training a classifier[14].

2.1.5 Word2Vec

The Word2Vec model extracts the notion of relatedness across words or products [8]. The Word2vec algorithm uses a NN(neural network) model to learn word associations from a large text corpus. After training the model, it can detect synonyms of words or suggest different words for sentence completion.

2.1.6 LDA(Topic Modelling)

Topic modelling [19] is one of the most potent techniques in text mining for data mining, latent data discovery, and finding relationships among data and text documents [11]. There are various methods for topic modeling; Latent Dirichlet Allocation (LDA) is one of the most popular in this field. Researchers have proposed multiple models based on the LDA in topic modeling. It is a generative statistical model that explains a set of observations through unobserved groups, and each group explains why some parts of the data are similar. It creates topics from similar words in a document.

2.1.7 TextBlob

TextBlob [15]is a Python library for processing textual data. It provides a simple API for diving into some beneficial natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and polarity scores [9].

2.2 Grading

2.2.1 Polarity Score

The polarity score is the score of a sentence between -1 to +1 which is scaled into three classes in our case. Positive if the polarity is above 0, negative if below 0 and neutral on 0 [4].

```
def polarity_scaling(polarity):
    """
        Scaling of polarity into three classes i.e. negative, positive and neutral.
    """
    # 0  nutral
    if polarity  == 0:
        return 0
    # greater then 0  positive
    elif polarity > 0:
        return 1
    else:
    # less then 0  negative
        return -1
```

Figure 2.1: Polarity scaling

2.2.2 Single Feature

Top five maximum polarity scores are considered as the best suggestions.

max(Polarity Scores of selected feature)

2.2.3 Multiple Features

Average of top five maximum polarity scores are considered as the best suggestions.

max(Average(Polarity Scores of multiple selected features))

2.3 Datasets

2.3.1 Online Datasets

- Amazon Date-set was based on star rating rating and reviews. Top 5 brands were compared in this data-set [10].
- GSMArena
- Twitter This data-set was used for comparing only 5 brands on 4 features i.e battery life, screen quality, operating system and brand [24].

2.3.2 FAST-NU Dataset

This data-set has multiple sources. It has mobile specifications and reviews of more than 6500+ mobiles of 100+ different brands.

Brands	No. of Mobiles	No. of Reviews
Apple	98	6,000+
Samsung	1,313	70,000+
Oppo	202	14,000+
Huawei	376	26,000+
Infinix	75	5,000+

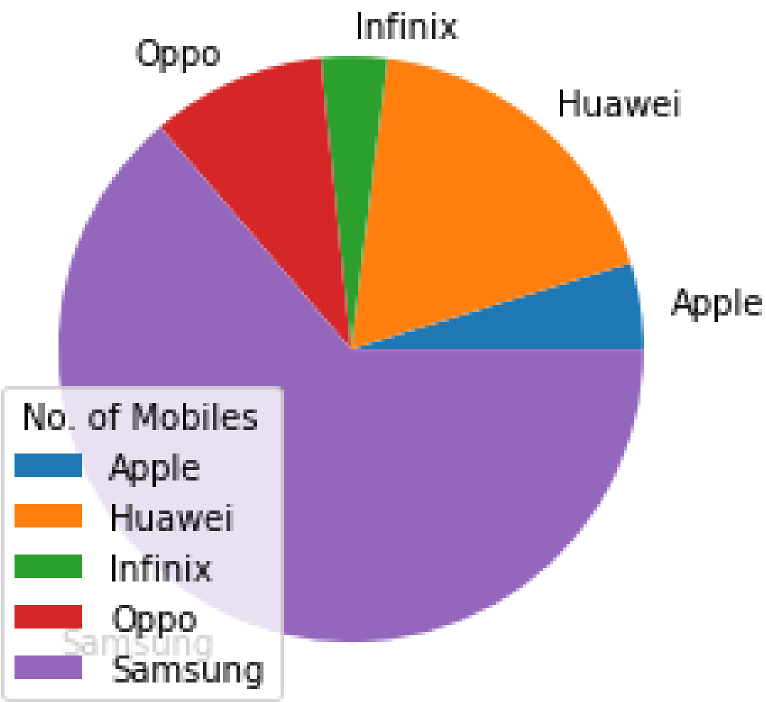


Figure 2.2: Pie Chart

Name	reviewer	review	Date	OS	cpu	Storage	Hits	Screen_siz	Screen_res	RAM
Apple iPhone 13 Pro Max	your moder	its has 1tb storage bruh the thing is most people use	2 hours ag	iOS 15 up	Hexa-core	128GB/25	3 792 981	6.7"	1284x277	6 GB RAM
Apple iPhone 13 Pro	John	John 12 Dec 2021Lol stop with the lies!	13-Dec-21	iOS 15 up	Hexa-core	128GB/25	1 533 621	6.1"	1170x253	6 GB RAM
Apple iPhone 13	your moder	so SUS Beacuse iphone 13 needs an upgrade man like	2 hours ag	iOS 15 up	Hexa-core	128GB/25	1 847 081	6.1"	1170x253	4 GB RAM
Apple iPhone 13 mini	John	Anonymous 07 Dec 2021ok but I wanted to buy a	12-Dec-21	iOS 15 up	Hexa-core	128GB/25	808 297 hi	5.4"	1080x234	4 GB RAM
Apple iPad mini (2021)	Aj	Can somebody help me to buy the better one overall	5 hours ag	iPadOS 15	Hexa-core	64GB/256	472 867 hi	8.3"	1488x226	4 GB RAM
Apple iPad 10.2 (2021)	Anonymous	If you want iPad with powerful performance donâ€™	09-Dec-21	iPadOS 15	Hexa-core	64GB/256	344 187 hi	10.2"	1620x216	3 GB RAM
Apple Watch Edition Series 7	Anonymous	Inst this the aple watch 7?	08-Oct-21	watchOS 8	Dual-core	32GB stora	58 410 hits	1.9"	484x396 pi	
Apple Watch Series 7	Anonymous	Very poor battery life. Substandard charger. The fas	########	watchOS 8	Dual-core	32GB stora	106 039 hi	1.9"	484x396 pi	
Apple Watch Series 7 Aluminum	Anonymous	with this battery life is for junk only	16-Oct-21	watchOS 8	Dual-core	32GB stora	187 498 hi	1.9"	484x396 pi	
Apple iPad Pro 12.9 (2021)	Anonymous	To the Apple please improve ipad os . I know your m1	10-Dec-21	iPadOS 14.	Octa-core	128GB/25	844 567 hi	12.9"	2048x273	8/16 GB RA
Apple iPad Pro 11 (2021)	Anonymous	Anonymous 18 Oct 2021do you want it to have a	########	iPadOS 14.	Octa-core	128GB/25	692 050 hi	11.0"	1668x238	8/16 GB RA
Apple iPhone 12 Pro Max	Anonymous	NeoGul 04 Dec 2021Anyone here had they phone st	07-Dec-21	iOS 14.1 u	Hexa-core	128GB/25	11 276 43	6.7"	1284x277	6 GB RAM
Apple iPhone 12 Pro	KC2FYA		23 hours a	iOS 14.1 u	Hexa-core	128GB/25	4 158 611	6.1"	1170x253	6 GB RAM
Apple iPhone 12	Anonymous	Anonymous 12 Dec 2021mines at 85% after a year A	6 hours ag	iOS 14.1 u	Hexa-core	64GB/128	5 478 172	6.1"	1170x253	4 GB RAM
Apple iPhone 12 mini	Anonymous	tri 29 Nov 2021i just upgrade to 12 mini from 11.. i	08-Dec-21	iOS 14.1 u	Hexa-core	64GB/128	3 843 010	5.4"	1080x234	4 GB RAM
Apple iPad Air (2020)	Anonymous	Anonymous 05 Oct 2020just pleeeease stop crying	13-Dec-21	iPadOS 14.	Hexa-core	64GB/256	1 420 752	10.9"	1640x236	4 GB RAM
Apple iPad 10.2 (2020)	Lolol	I'm still using it after 12 months and I only charge it	########	iPadOS 14	Hexa-core	32GB/128	1 079 356	10.2"	1620x216	3 GB RAM
Apple Watch SE	Sid	Sid 02 Dec 2021I've been using the SE cellular varian	09-Dec-21	watchOS 7	Dual-core	32GB stora	479 599 hi	1.78"	448x368 pi	1 GB RAM
Apple Watch Series 6 Aluminum	EKispert	Anonymous 03 Jun 2021Series 6 watch cost 136 US	25-Jul-21	watchOS 7	Dual-core	32GB stora	253 270 hi	1.78"	448x368 pi	1 GB RAM
Apple Watch Series 6	anan	can iphone series 6 support to version 6 s plus 12.5.5	25-Oct-21	watchOS 7	Dual-core	32GB stora	419 519 hi	1.78"	448x368 pi	1 GB RAM
Apple Watch Edition Series 6	range	Anonymous 05 May 2021The design has become so	########	watchOS 7	Dual-core	32GB stora	144 015 hi	1.78"	448x368 pi	1 GB RAM
Apple iPhone SE (2020)	kaveh	really good phone battery life is ok be consider batte	12-Dec-21	iOS 13 up	Hexa-core	64GB/128	6 864 903	4.7"	750x1334	3 GB RAM
Apple iPad Pro 12.9 (2020)	Takis	Sheesh 15 Jul 2021A12z is more powerful than a14N	########	iPadOS 13.	Octa-core	128GB/25	1 395 177	12.9"	2048x273	6 GB RAM
Apple iPad Pro 11 (2020)	Devonte	Najib1312 23 Jul 2021Guys pls help me choose.	20-Aug-21	iPadOS 13.	Octa-core	128GB/25	1 269 773	11.0"	1668x238	6 GB RAM
Apple iPhone 11 Pro Max	John	Anonymous 20 Oct 2021I personally thinks itâ€™s th	11-Dec-21	iOS 13 up	Hexa-core	64GB/256	9 853 722	6.5"	1242x268	4 GB RAM
Apple iPhone 11 Pro	Anonymous	11pro is the best compect phone till now	########	iOS 13 up	Hexa-core	64GB/256	6 418 120	5.8"	1125x243	4 GB RAM
Apple iPhone 11	ping koi balah angui	Anonymous 12 Dec 2021I'm on ios 14.4 version but	7 hours ag	iOS 13 up	Hexa-core	64GB/128	10 768 85	6.1"	828x1792	4 GB RAM

Figure 2.3: Data-set Sample

2.4 Conclusion:

We studied several techniques. One good option to choose the best plan was to use each method for whole data, but we concluded that by using ensemble learning, we could achieve better results by combining results of SVM and Naive Bayes Classifier as the data is divers [17].

Chapter 3

Implementation

3.1 Data

During the initial stage of the project, we scraped data from an online website GSMArena [1] which had reviews of almost 10,000 different mobiles with different brands including 100+ brands and 6500+ mobiles.

```
def extract_smartphone_infos(network, smartphone):
    smartphone_dict = dict()
    smartphone = smartphone.find("a")
    url_smartphone = f"https://www.gsmarena.com/{str(smartphone['href'])}"
    logger.debug("url_smartphone : %s", url_smartphone)
    smartphone_dict["Link"] = url_smartphone
    smartphone_dict["Image"] = str(smartphone.find("img")["src"])
    soup_smartphone = network.get_soup(url_smartphone)
    smartphone_dict["Name"] = str(
        soup_smartphone.find("h1").find_all(text=True, recursive=False)[0]
    )
    logger.info(f"Processing model {smartphone_dict['Name']}")

    if soup_smartphone.select("td", {"class": "nfo"}):
        smartphone_dict["Release date"] = soup_smartphone.find(
            "span", {"data-spec": "released-hl"}
        ).text.strip()
        smartphone_dict["Weight"] = soup_smartphone.find(
            "span", {"data-spec": "body-hl"}
        ).text.strip()
        smartphone_dict["OS"] = soup_smartphone.find(
            "span", {"data-spec": "os-hl"}
        ).text.strip()
        smartphone_dict["Storage"] = soup_smartphone.find(
            "span", {"data-spec": "storage-hl"}
        ).text.strip()
        smartphone_dict["Fans"] = str(
            soup_smartphone.find("li", {"class": "help-fans"})
            .find("strong")
            .find(text=True)
        ).strip()
      smartphone_dict["Popularity"] = str(
          soup_smartphone.find("li", {"class": "help-popularity"}).find_all(
              text=True
          )[2]
      ).strip()
      smartphone_dict["Hits"] = str(
          soup_smartphone.find("li", {"class": "help-popularity"}).find_all(
              text=True
          )[4]
      ).strip()
      ecran = soup_smartphone.find("li", {"class": "help-display"}).find_all(
          text=True
      )
      if ecran:
          try:
              logger.debug("Screen : %s", ecran)
              smartphone_dict["Screen_size"] = str(ecran[2]).strip()
              smartphone_dict["Screen_resolution"] = str(ecran[3]).strip()
          except Exception as e:
              logger.debug("Screen : %s", e)
      ram = soup_smartphone.find("li", {"class": "help-expansion"}).find_all(
          text=True
      )
```

Figure 3.1: Data Scraping 1

```python
def extract_brand_name(brand):
    return brand["href"].rsplit("-", 1)[0]


def extract_brand_infos(network, brand):
    index_page = 1
    brand = brand["href"].rsplit("-", 1)
    brand_name = str(brand[0])
    brand_id = str(brand[1].split(".")[0])
    logger.info(f"Processing brand {brand_name}")
    url_brand_base = f"https://www.gsmarena.com/{brand_name}-f-{brand_id}-0"
    smartphone_list = []

    while True:
        url_brand_page = f"{url_brand_base}-p{index_page}.php"
        logger.debug(url_brand_page)
        index_page = index_page + 1
        soup_page = network.get_soup(url_brand_page)
        logger.debug(f"Page URL : {url_brand_page}")

        if soup_page.find("div", {"class": "section-body"}).select("li"):
            smartphones = soup_page.find(
                "div", {"class": "section-body"}
            ).find_all("li")
            soup_page.decompose()
            for smartphone in smartphones:
                smartphone_dict = extract_smartphone_infos(network, smartphone)
                smartphone_list.append(smartphone_dict)
        else:
            soup_page.decompose()
            logger.error(
                "%s : td class=section-body not found", url_brand_page
            )
            return smartphone_list
```

Figure 3.2: Data Scraping 2

For Data Scraping we used the python library BeautifulSoup [23]. Data for mobile phones consists of features, reviews' details and ratings.

We labeled our data into three categories.

Labels are:

- Positive: Polarity score above 0
- Neutral: Polarity score equals to 0
- Negative: Polarity score less than 0

3.2 Models

We trained different models with various accuracy measures, but SVM and Naive Bayes gave us comparatively good results. In some cases, SVM had better accuracy, but in other cases, Naive Bayes was better as the data had diversity, so we ensemble the results of both models to generate our final output. We used Majority Voting Ensemble for that purpose.

3.2.1 Pre-Processing

We have to do some pre-processing to train any model on a data set. Pre-processing involves data cleaning, tokenization, removing stop words, POS tagging and more [13]. In our case, we performed multiple techniques to get the required data.

First, we removed special characters, single characters and multiple spaces, as shown below.

```
def pre_process(sentence):
    """
        i) Remove special characters.
        ii) Remove single characters.
        iii) Replace multiple spaces with single spaces.
    """


    # Remove all the special characters
    processed_sentence = re.sub(r'\W', ' ', str(sentence))

    # remove all single characters
    processed_sentence = re.sub(r'\s+[a-zA-Z]\s+', ' ', processed_sentence)

    # Remove single characters from the start
    processed_sentence= re.sub(r'\^[a-zA-Z]\s+', ' ', processed_sentence)

    # Substituting multiple spaces with single space
    processed_sentence= re.sub(r'\s+', ' ', processed_sentence, flags=re.I)

    # Removing prefixed 'b'
    processed_sentence = re.sub(r'^b\s+', '', processed_sentence)


    return processed_sentence
```

Figure 3.3: Pre-processing 1

- Setting lower case for all the text.
- Stemming each sentence.
- Tokenizing.
- Removing Stop-words.

```
def updated_sentence(sentence):
    """
        i) Lower cases the sentence.
        ii) Sentence stemming.
        iii) Tokenization of sentence.
        iv) Stop-words removal.
        v) Returns list after all above operations.
    """
    sentence = sentence.lower()
    new = " "
    p = PorterStemmer()
    processed = pre_process(sentence)
    stemmed = p.stem(processed)
    tokens = tokenize(stemmed.strip())
    lst=list(tokens)
    lst2 = []
    for i in lst:
        #using nltk dic for stopwords
        if  i not in stopwords :
            lst2.append(i)
    return (new.join(lst2))
```

Figure 3.4: Pre-processing 2

- Removing none keyword from text.
- Removing tabs and new lines.
- Polarity calculation.
- Creating review-polarity tuple.

```
def reviews_list_polarity():
    """
        i) Removes none keyword from sentence.
        ii) Removes tabs and newlines from sentence.
        iii) Calculates polarity of each sentence.
        iv) Creates a tuple (review,polarity).
        v) Adds tuples to a dictionary.
    """

    individual_review = []
    for_reviews = []
    for_polarity = []
    updated_review_Dict = {}
    super_list_2 = []
    super_list = listing()
    for remove_none_type in super_list:
        if remove_none_type is not None:
            super_list_2.append(remove_none_type)
    for select_list in super_list_2:
        for i in select_list:
            news =i.strip()
            new1=news.split(".")

            lst_list = []
            lst_list_2 = []


            for j in new1:
                j = updated_sentence(j)
                temp =j.replace("\r\n" ,"")
                pol = TextBlob(temp).sentiment.polarity
                polarity=polarity_scaling(pol)
                tup = (temp ,polarity)
                lst_list.append(tup)
            for remove_tuple in lst_list:
                if remove_tuple != ('',0):
                    lst_list_2.append(remove_tuple)
            if lst_list_2 != []:
                for_reviews.append(lst_list_2[0][0])
                for_polarity.append(lst_list_2[0][1])
    updated_review_Dict["reviews"]=for_reviews
    updated_review_Dict["polarity"]=for_polarity
    return updated_review_Dict
```

Figure 3.5: Pre-processing 3

3.2.2 Model Training

We trained two different models on our data-set which includes SVM and Naive Bayes.

```
data=pd.DataFrame(reviews_list_polarity())
# spiting data for train data
x = data['reviews']
y = data['polarity']#text blob computed
```

```
vec = TfidfVectorizer()
matrix_X = vec.fit_transform(x)
```

```
train_x=matrix_X[:8000]
train_y=y[:8000]
NB_model = MultinomialNB()
NB_model.fit(train_x,train_y)
```

```
MultinomialNB()
```

```
pred_x=matrix_X[8000:]
pred_y=y[8000:]
pred=NB_model.predict(pred_x)
```

Figure 3.6: Training Model (Naive Bayes)

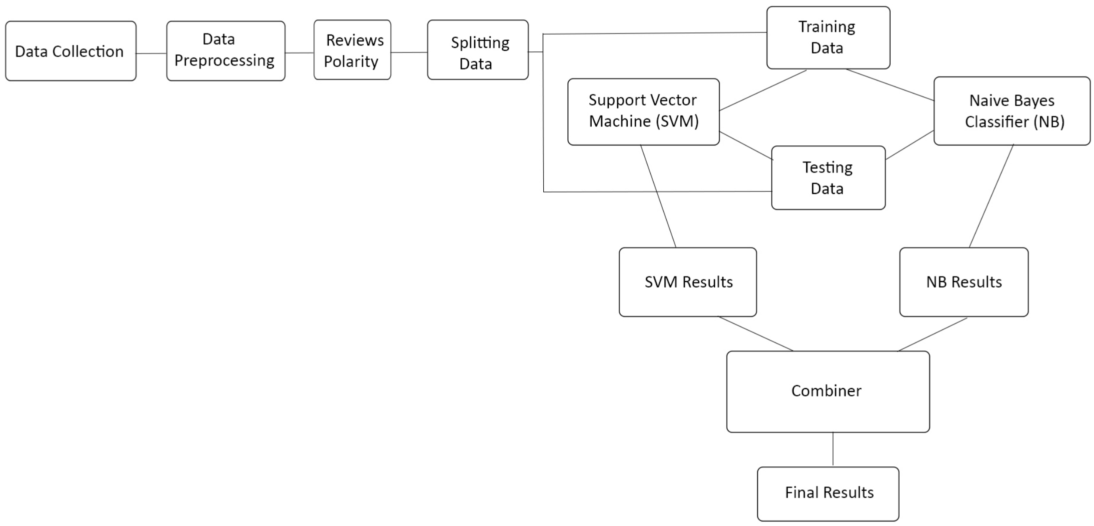
```
train_x_svm=matrix_X[:8000]
train_y_svm=y[:8000]
svm_model = SVC(kernel='linear')
svm_model.fit(train_x_svm,train_y_svm)
```

```
SVC(kernel='linear')
```

```
pred_x_svm=matrix_X[8000:]
pred_y_svm=y[8000:]
pred_svm=svm_model.predict(pred_x_svm)
```

Figure 3.7: Training Model (SVM)

3.3 Methodology



Architecture of Review Based Analysis of Mobile Phones

Figure 3.8: Methodology

3.4 Analysis and Design

Use Cases:

1) Register/Login

Name: Register/Login

Goal: User login or user registration.

Actors: User

Pre-conditions: For user login, user must be registered.

Basic Flow: User will register himself and after registration he will login.

Post conditions: After login user will select the features.

2) Provides Requirements

Name: Provides Requirements

Goal: User will provide specific requirements.

Actors: User

Pre-conditions: User will login.

Basic Flow: User will select the features from given list of features.

Post conditions: Selected features will be processed.

3) View Results:

Name: View Results

Goal: User will get results based on his requirements.

Actors: User

Pre-conditions: At least one feature must be selected.

Basic Flow: User will see the top results according to his search.

Post conditions: User will be redirected to feedback.

4) Submit Feedback:

Name: Submit Feedback

Goal: User will submit his experience with system.

Actors: User

Pre-conditions: View Results.

Basic Flow: User will enter his opinion in a text box and submit.

Post conditions: User will be redirected to main page.

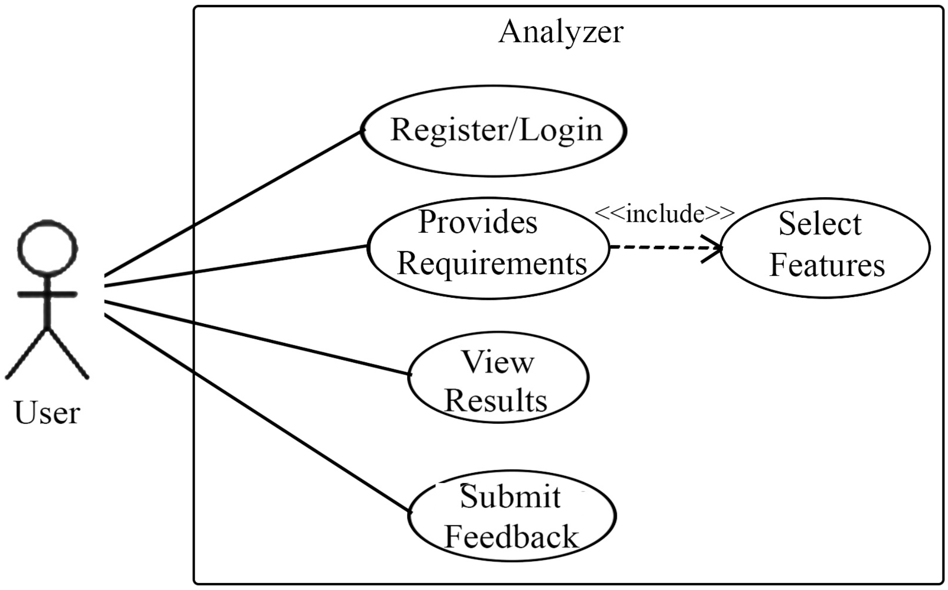


Figure 3.9: Use Case Diagram

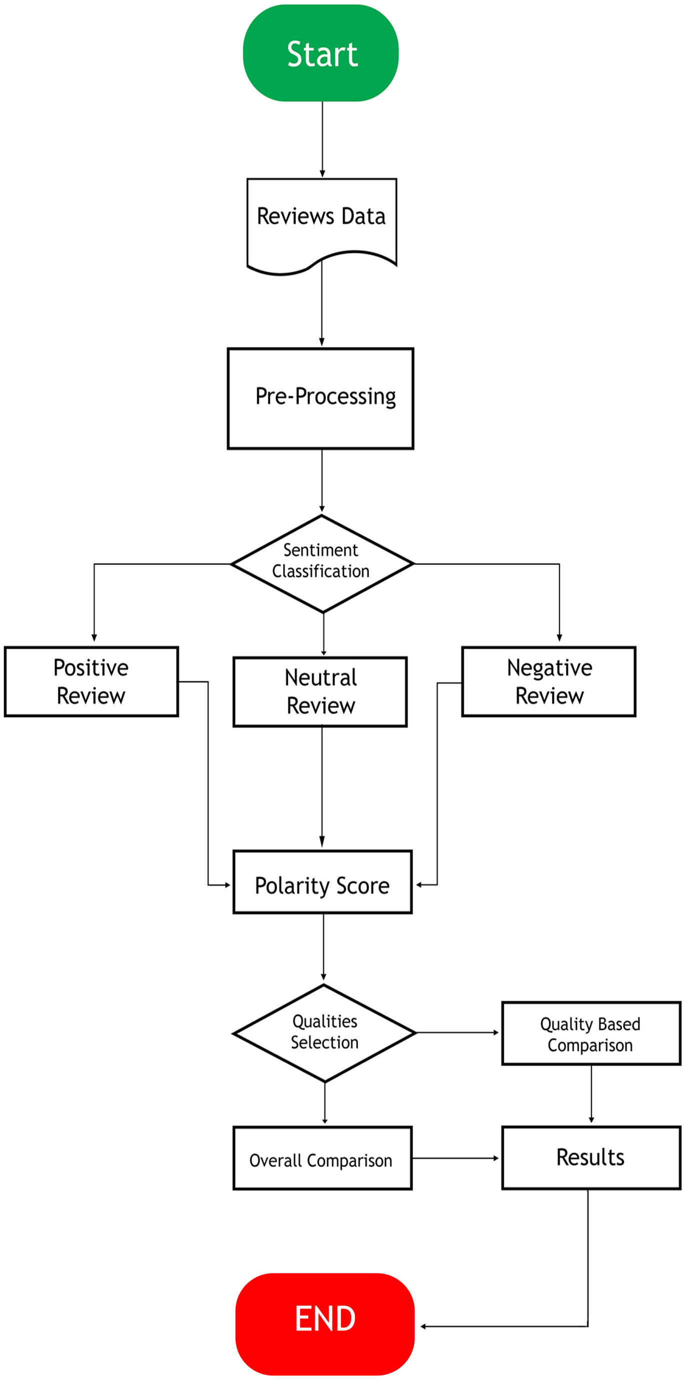


Figure 3.10: Flow Chart

3.5 Front-End

For front-end we used web framework React [7]. The front-end display of application is simple and consists of basic operations and search functionality.

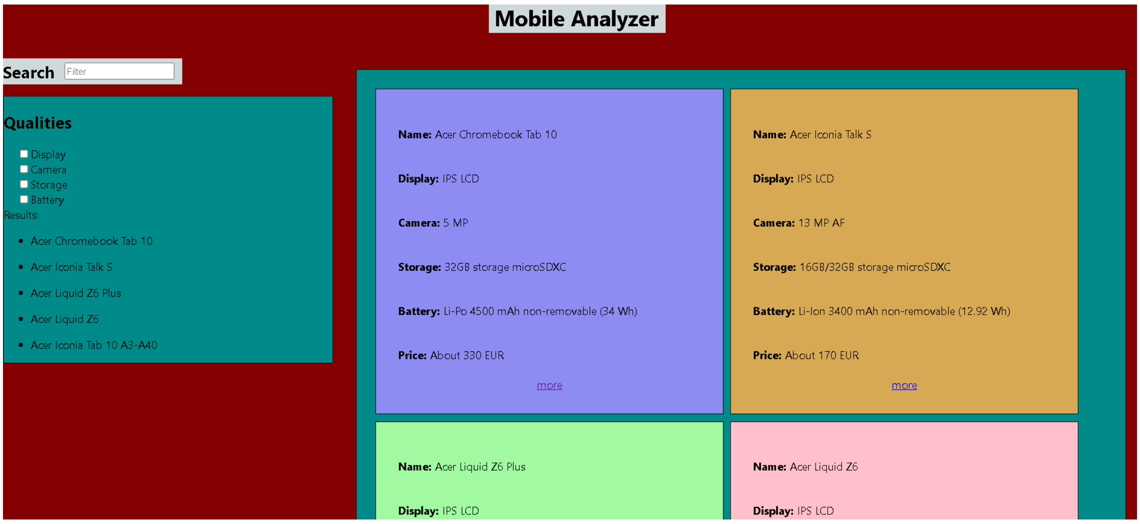


Figure 3.11: Front-End

Chapter 4

Results

4.1 Polarity Results

4.1.1 Evaluation

For the evaluation of the models, confusion matrix [16] and heat map is used that will give us accuracy measures of both models.

With 76% accuracy Of the Naive Bayes Model Shows the actual polarity score with the predicted polarity score resulting in the Figures 4.1 and 4.2.

```
Naive Bayes Matrix , accuracy and f1-score


NB confusion matrix :
 [[ 1477 11727  6750]
 [     2 75741  3624]
 [     1 15144 41689]]
              precision    recall  f1-score   support

          -1       1.00      0.07      0.14     19954
           0       0.74      0.95      0.83     79367
           1       0.80      0.73      0.77     56834

    accuracy                           0.76    156155
   macro avg       0.85      0.59      0.58    156155
weighted avg       0.79      0.76      0.72    156155

Accuracy of Model:  0.7614677724056226
```

Figure 4.1: Naive Bayes Confusion Matrix

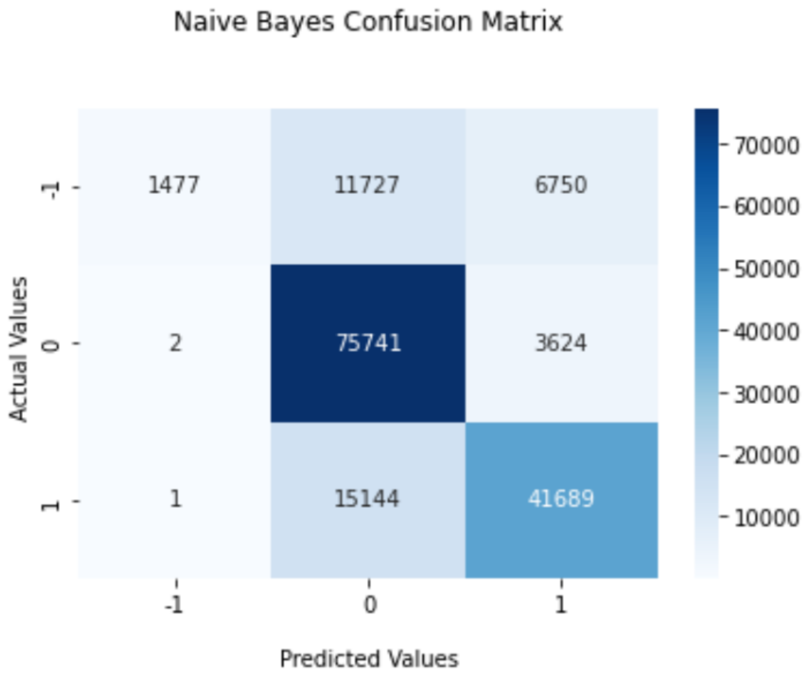


Figure 4.2: Naive Bayes Heat Map

With 89% accuracy Of SVM model Shows the actual polarity score with the predicted polarity score resulting in Figures 4.3 and 4.4.

```
SVM Matrix , accuracy and f1-score


SVm confusion matrix :
 [[12530  5935  1489]
 [  107 78837   423]
 [  831  7875 48128]]
              precision    recall  f1-score   support

          -1       1.00      0.07      0.14     19954
           0       0.74      0.95      0.83     79367
           1       0.80      0.73      0.77     56834

    accuracy                           0.76    156155
   macro avg       0.85      0.59      0.58    156155
weighted avg       0.79      0.76      0.72    156155

Accuracy of Model :  0.8933111331689667
```

Figure 4.3: SVM Confusion Matrix

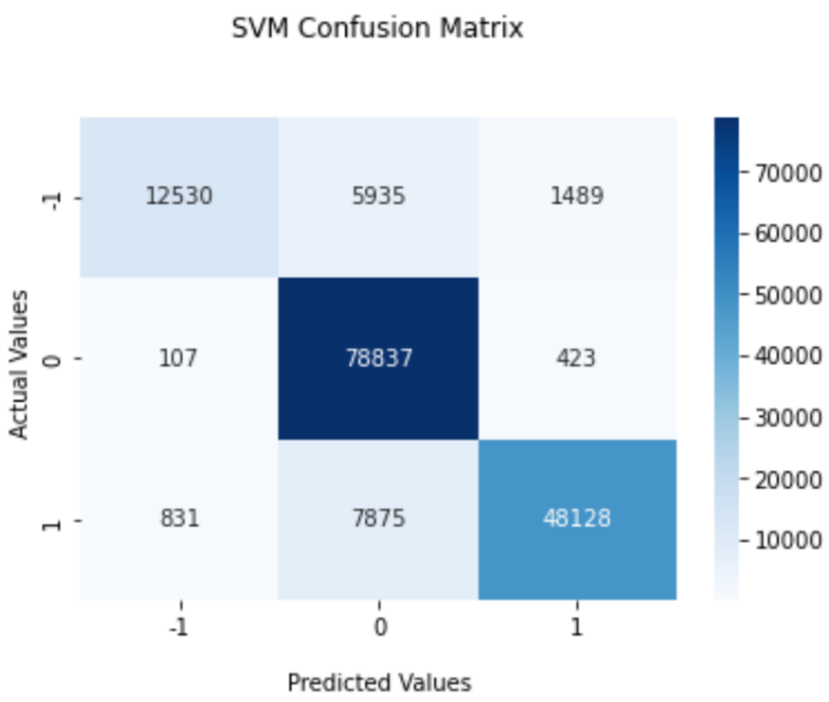


Figure 4.4: SVM Heat Map

4.1.2 Polarity Scores for Features

Polarity score of each review according to features are calculated in positive(1), neutral(0) or negative(-1) and contained in a list. Each mobile phone has a list for polarity scores of all reviews.

	reviews	polarity	battery_polarity	display_polarity	storage_polarity	camera_polarity
0	[screen easily worthy device ipad users want t...	[1, 0, -1, 0, 0, 0, -1]	[0]	[1, 0, 0, -1, 0, 0]	[0, -1, -1]	[0]
1	[would pretty embarrasing use tablet purposes ...	[1, 1, 1, -1, -1, -1, 1, -1]	[1, 1]	[1]	[1, 1, 1, 1]	[-1, -1, -1, -1, 1, 0]
2	[indeed charging pot complet, bought phone dec...	[0, 1, -1, 0, 0, 0, 0, 1, 0, 0, 0]	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[-1, -1, 1, 1, 0, 1]	[1, 0]	[-1, 0]
3	[edge screen fell part part, excellent phone c...	[0, 1, 1]	[1]	[0, 0, 0, 1, 1]	[1, 1]	[0]
4	[nwith unique looks hdmi fhd screen speakers m...	[1, 1, 0, 1, 1]	[1, 1]	[1, 1, 1]	[1, 1, 1, 0]	[0]

Figure 4.5: Polarity Score with features

After getting all the polarities of the reviews, sum of all scores for each mobile phone is calculated.


```
{
    "Link": "https://www.gsmarena.com/acer_chromebook_tab_10-9139.php",
    "Name": "Acer Chromebook Tab 10",
    "Price": "69910",
    "polarity": "[1, 0, -1, 0, 0, 0, -1]",
    "battery_polarity": "[0]",
    "display_polarity": "[1, 0, 0, -1, 0, 0]",
    "storage_polarity": "[0, -1, -1]",
    "camera_polarity": "[0]",
    "battery_sum": "0",
    "display_sum": "0",
    "storage_sum": "-2",
    "camera_sum": "0"
},
```

```
{
    "Link": "https://www.gsmarena.com/acer_liquid_z6_plus-8305.php",
    "Name": "Acer Liquid Z6 Plus",
    "Price": "52962",
    "polarity": "[0, 1, -1, 0, 0, 0, 0, 1, 0, 0, 0]",
    "battery_polarity": "[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]",
    "display_polarity": "[-1, -1, 1, 1, 0, 1]",
    "storage_polarity": "[1, 0]",
    "camera_polarity": "[-1, 0]",
    "battery_sum": "0",
    "display_sum": "1",
    "storage_sum": "1",
    "camera_sum": "-1"
},
```

```
{
    "Link": "https://www.gsmarena.com/acer_iconia_talk_s-8306.php",
    "Name": "Acer Iconia Talk S",
    "Price": "36014",
    "polarity": "[1, 1, 1, -1, -1, -1, 1, -1]",
    "battery_polarity": "[1, 1]",
    "display_polarity": "[1]",
    "storage_polarity": "[1, 1, 1, 1]",
    "camera_polarity": "[-1, -1, -1, -1, 1, 0]",
    "battery_sum": "2",
    "display_sum": "1",
    "storage_sum": "4",
    "camera_sum": "-3"
},
```

```
{
    "Link": "https://www.gsmarena.com/acer_liquid_z6-8304.php",
    "Name": "Acer Liquid Z6",
    "Price": "25421",
    "polarity": "[0, 1, 1]",
    "battery_polarity": "[1]",
    "display_polarity": "[0, 0, 0, 1, 1]",
    "storage_polarity": "[1, 1]",
    "camera_polarity": "[0]",
    "battery_sum": "1",
    "display_sum": "2",
    "storage_sum": "2",
    "camera_sum": "0"
},
```


Figure 4.6: Sum of polarity scores

4.2 Front-end Results

Figure 4.7: Results for single feature

Figure 4.8: Results for multiple features

Final results are concluded on the basis of selected features. One or multiple features can be selected at the same time. The top five suggestions are calculated on top five polarity scores. In case of multiple features the average of polarity scores of the selected features are calculated and top five are presented as results.

Chapter 5

Discussion

The primary purpose of our project was to achieve such an automated system that can reduce time spent on mobile phone analysis. To achieve that goal, we trained multiple models, and after analyzing the results, we achieved our goal of getting the results. The results shown in chapter 4 are pretty according to our goals. In the results, the top suggestions are calculated on the basis of selected features, and their polarity scores are based on the reviews dropped by different reviewers. The mobile phones with a higher sum of polarity scores are considered to be the best suggestions.

Chapter 6

Conclusions and Future Work

In the future, It would be interesting to perform further analysis based on the brands and added qualities in the future. We can also look at building a model to predict the review's helpfulness or extracting each brand's top products. Some future works and modifications are described below:

- Nowadays, posting reviews with fake accounts is prevalent, so in the extension of our project, we can filter out the fake reviews that are posted by fake accounts[5].
- More features can be added to the features list for analysis.
- Self-generated features can be added based on reviews. Topic modeling has recently gained popularity in generating topics from different documents.
- Other intelligent products like smartwatches, Tabs and laptops can be added to data-set for analysis with dynamic feature selection options.

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