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CENG 407
Sentiment Analysis of the Feedback from Airplane Passengers

PROJECT REPORT

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Contents

1. Literature Review

Abstract

The enlargement of the internet environment in recent years has provided us researchers with a great data opportunity. Nowadays, many people can share their opinions on many issues such as a service, a product, or an event through social media accounts such as Twitter, Facebook, Instagram, etc. In some cases, it is difficult for people to read and interpret all of these comments because they are too many. For this reason, we will make a sentiment analysis on Twitter data, which is one of the most frequently commented social media accounts. We will perform this analysis based on the comments made by the passengers on Twitter as a result of the services provided by American airports to their passengers. During about this researches, various methods and algorithms have been tried. In this report, we will share the research we made to use more accurate methods and algorithms in our project process. You can examine the details of our research in the following sections.

2. Introduction

Working on sentiment analysis continues today and is used in many areas. Today, there is a lot of data on social media as social media is used by many people. People share their thoughts on many issues through their social media accounts. Sentiment analysis is needed because the comments in some posts are too many to read and decide on all of them. These data are generally classified as positive, negative, and neutral, making it easier for institutions and people doing research. Institutions can make improvements in their products or services based on these analyzes. People can also make a more accurate decision based on these analyzes at the product purchase stage. We will determine the level of satisfaction by analyzing the comments made by the American airport passengers on Twitter about the service they receive. During these analyzes, Machine Learning algorithms such as Support Vector Machine, Maximum Entropy, Bayesian Network ,Neural Network, Naïve Bayes, , are generally used. You can examine the work done with these algorithms, their usage, and efficiency in the following sections.

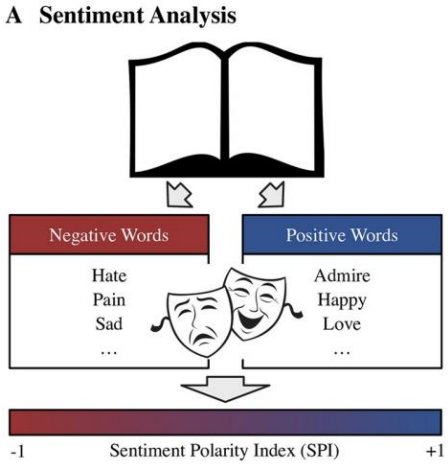

Figure 1. A Sentiment Analysis [15]

3. Sentiment Analysis

Sentiment analysis is a subject, company or product etc. classify them as good, bad or neutral by examining and researching their comments. As a result, it gives feedback to the employees on the subject being researched.

Manually studying large data is difficult for workers without AI helping, and survey studies may not give reliable results. In social media, people make millions of comments every day and share them subjectively. Sentiment analysis allows us to reach big data in a short time. Moreover, since the comments are subjective, we get reliable information and feedback on that topic from the primary source.

4. Problem Definition of Sentiment Analysis

In this chapter, we focus on the problem definition of Sentiment Analysis or opinion mining. Problem definition is important to understand it's solutions.

4.1. Opinion Definition

The most important feature of our opinions and thoughts is that they are subjective. The reason is that they contain only the commenter's thoughts. Therefore, researchers or product sellers collect much more person's opinions and try to understand what society generally thinks.

It is also reliable in terms of assessment and evaluation, and since many people from many platforms with Twitter, Facebook, and forum applications express their opinions and thoughts that they share every day, we have a lot of opinion data on that topic.

Twitter posts have short sentences compared to other forum comments and include some internet slangs in these sentences. But It is also easy to review this data because it is short. Because these comments are short, it means that they do not contain too much unnecessary information rather than forum applications.

Tweets have been useful for users with these features. We will also use Twitter comments for sentiment analysis in our project.

4.1.1. Sentiment Analysis Tasks

An example is given to explain this analysis.

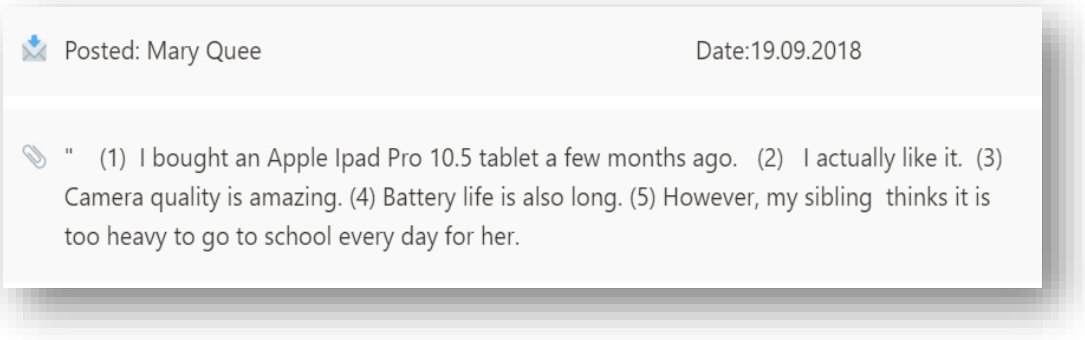

Figure 2. An Example of Sentiment Analysis

This tweet contains several positive, negative comments for the Apple Ipad Pro 10.5. Sentence (2) contains a generally positive opinion. Sentence (3) makes a positive comment about the camera quality of the Apple Ipad Pro. Sentence (4) makes a negative comment on battery. Sentence (5) contains a negative opinion about tablet's weight feature. However, this negative opinion in the sentence (5) belongs to the commenter's sibling.

This sample tweet actually gives us pretty good information about the structure of the comments. The Apple Ipad Pro 10.5 actually has many features such as camera quality, size, battery life, and individual comments that can be made for all of them. Also, as it appears in the sentence (5), it is important to whom the opinion belongs. Because the opinion in this sentence belongs to the commenter's sibling and does not belong to him/her. So we must know who the opinion belongs to. A complex definition makes it difficult to solve the problem. We use the opinion "**quintuple**" structure to symbolize it. [1]

$$(e_i, a_{ij}, s_{ijkl}, h_k, t_l) ;$$

- where *ei* is the name of an **entity**,

- *aij* is an **aspect** of *ei*,
- *sijkl* is t**he sentiment** on aspect *aij* of entity *ei*,
- *hk* is the opinion **holder** and
- *tl* is **the time** when the opinion is expressed by *hk*.
- d is given an opinion **document**

We intentionally use subscripts here. In this formula, subscripts are used to emphasize that the five parts of information .All of them depends on each other.That means that the opinion sijkl must be given by opinion holder hk about aspect aij of entity ei at time tl. [1]

In this example,

- Apple Ipad Pro represents entity e.
- Camera quality (a11) and battery life (a12) represents entity e of aspects.
- s111 of the sentiment on aspect a11 (Camera quality) of entity e1 and it is possitive and s112 of the sentiment on aspect a12 (battery life) of entity e1 and it is also possitive .
- The opinion holder is double. First one is Mary Quee (h1) who share its opinion on web and the second is her sibling (h2).

Suppose a viewpoint named d is given, let's discover all five fives in d (ei, aij, sijkl, hk, tl). [2][3][4]

Keys derived from the 5 parts. First part is entity. That is, we have to extract entities. The topic is pretty same to named entity recognition in information extraction [5]. For this reason, extraction itself is issue.

After extraction, we also have to categorize the extracted entities. In natural language text, people often write the same entity in different ways and that is also a problem. For example, “similar” word may be written as “same”, “identical”, and “homonym”. We have recognize all same meaning words.

4.1.2. Opinion Document

An opinion document is d, expressed as {e1, e2, ..., er} their views on some entities at a given time, the point containing a subset of the opinions {h1, h2, ..., hp} of some opinion holders.

We summarize all these concepts in 6 main tasks: [1]

1. Entities extraction
2. Aspects extraction
3. Opinion holders extraction and categorization
4. Time extraction , and also standardization
5. Aspect sentiment analysis classification
6. Opinion quintuple generation by formula

Sometimes more than one word can represent an entity. We should define both of them as the same entity and analyse it truly. But this rich feature of language poses a problem in sentiment analysis. The same problem applies to aspects. For instance, picture, image, and photo represent the same aspect. This is a problem of sentiment analysis.

5. Sentiment Classification

Sentiment analysis examined with three different levels:

1. **Document Level:** Examines the entire opinion document. It decides what emotion the document expresses. It is to be classified as positive or negative. This level of analysis assumes that each document expresses ideas about a single entity.
2. **Sentence Level:** The task at this level examines the sentences. Then he decides whether each sentence is positive or negative or neutral. Many objective sentences can imply ideas. Thus, it can be inferred that subjectivity is not the same as sensitivity. However, the item level is still not sufficient.
3. **Entity and Aspect Level:** Document level and sentence level analysis cannot accurately determine what people like and dislike. For example, the sentence "I still love this restaurant even though the service is not that good" was uttered in a positive tone, but we cannot infer that it is positive. As a result, there are two different types of views. The first of these is regular views and the second is comparative views.

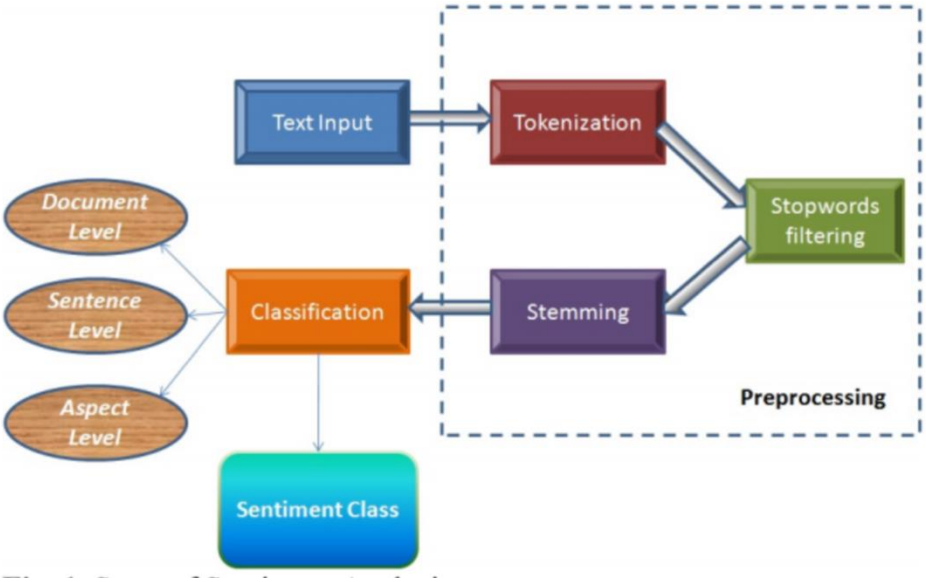

Figure 3. Steps of Sentiment Analysis [11]

An emotion dictionary is required for sentiment analysis. However, this alone is not enough. Below you can see some of the reasons for this.

1. Emotion words can be in opposite directions in different application areas.
2. A sentence may not express any emotion.
3. Sarcastic phrases are hard to handle.
4. Many sentences that do not contain sensitive words can also imply people's opinions.
5. Idea spam has become a major problem. There are people giving fake ideas in reviews and forum discussions. Some companies write fake reviews and fake blogs to attract customers. This is an important problem for analysis.

5.1. Document Sentiment Classification

Problem Definition: Let's assume that an opinion document is given that evaluates a company. In such a case, the general opinion of the opinion holder about the company should be determined.

Assumption: Let's assume that one opinion document evaluates more than one company. Opinions on different companies may differ. Also, since the views of multiple viewers may differ, it is not logical for these observers to express their views in one document, that is, in the same document.

5.2. Classification of Sentiment Using Supervised Learning Methods

Classification of sentiment is generally categorized as a classification problem in different categories, positive and negative. The neutral class can be used, but most research does not use a neutral class. The neutral class can be used, but not using this class significantly eases the classification problem. We will use the neutral class in our project. In traditional text classification, related words are key features. However, opinion words expressing opinions according to different emotional states are important. This is a text classification problem. For this reason, one of the controlled learning methods such as naive bayes classification, and support vector machines can be used. For example, this approach has been used by some researchers to categorize film criticism into two

categories, positive and negative. [7] Terms and their frequency, part of speech in Figure 1, rules of opinions, sentiment shifters, syntactic dependency are some of these sample features. [1][6]

Tag	Description	Tag	Description
CC	Coordinating conjunction	PRP$	Possessive pronoun
CD	Cardinal number	RB	Adverb
DT	Determiner	RBR	Adverb, comparative
EX	Existential *there*	RBS	Adverb, superlative
FW	Foreign word	RP	Particle
IN	Preposition or subordinating conjunction	SYM	Symbol
JJ	Adjective	TO	*to*
JJR	Adjective, comparative	UH	Interjection
JJS	Adjective, superlative	VB	Verb, base form
LS	List item marker	VBD	Verb, past tense
MD	Modal	VBG	Verb, gerund or present participle
NN	Noun, singular or mass	VBN	Verb, past participle
NNS	Noun, plural	VBP	Verb, non-3rd person singular present
NNP	Proper noun, singular	VBZ	Verb, 3rd person singular present
NNPS	Proper noun, plural	WDT	Wh-determiner
PDT	Predeterminer	WP	Wh-pronoun
POS	Possessive ending	WP$	Possessive wh-pronoun
PRP	Personal pronoun	WRB	Wh-adverb

Figure 4. Penn Treebank Part Of Speech Tags [1]

Classifies ideas according to some fixed syntactic patterns used to explain ideas. Syntax patterns are created based on the part of speech tags.

5.3. Sentiment Rating Prediction

Not all researchers solve this problem using regression techniques. However, since the ranking scores are listed, the issue can be specified like regression problem. The graphical method improves the ratings by solving and revising the optimization problem to ensure that they are uniform throughout the graph in terms of both ratings and link weights. There have been researchers who presented a different view from the traditional bag representation word. [8] This view provided a bag document representation for determining strength for n-grams with ideas. Each of the views is classified as sentiment word, modifier and negator. As an example, in a sentence as "not very good", sentiment word is "good", modifier is "very" and negator is "not". Knowing these addictions is useful for accuracy.

5.4. Cross-Domain Sentiment Classification

Same words for a field can have a positive meaning and negative for a different field. The authors suggested that emotion classifiers should be transferred to new areas when there is no large amount of tagged data in these areas. [13]
Tried four different strategies:

1. Training and testing in the target area on a mix of tagged reviews from other areas where such data are available.
2. The feature set can only be limited to those observed in the target area to train a classifier.
3. Using classifier compilations from fields with existing tagged data, these can be tested in the target area.
4. The small number of tagged data in the target area can be combined with large amounts of untagged data.

SVM was used for the first three strategies. For the fourth strategy, EM was used for semi-supervised learning [12]. As a result of their experiments, they observed that the 4th strategy showed the best performance. This is because it showed that it can use both tagged and untagged data in the target area.

5.5. Classification of Cross-Language Sentiment

This type sensitivity classification refers to the sensitivity opinion-expressing classification articles in more than one language, but we will make our classifications on a common language, English.

6. Approaches for Sentiment Analysis

Sentiment analysis uses Lexicon Based (LB) or Machine Learning (ML) methods. The words are ranked by grouping according to their polarity using the LB method. After the scores obtained from the relevant document are added, a conclusion is reached. In another method, ML methods, the texts are classified and sentiment estimation is made. [9] We will use machine learning methods while continuing our project.

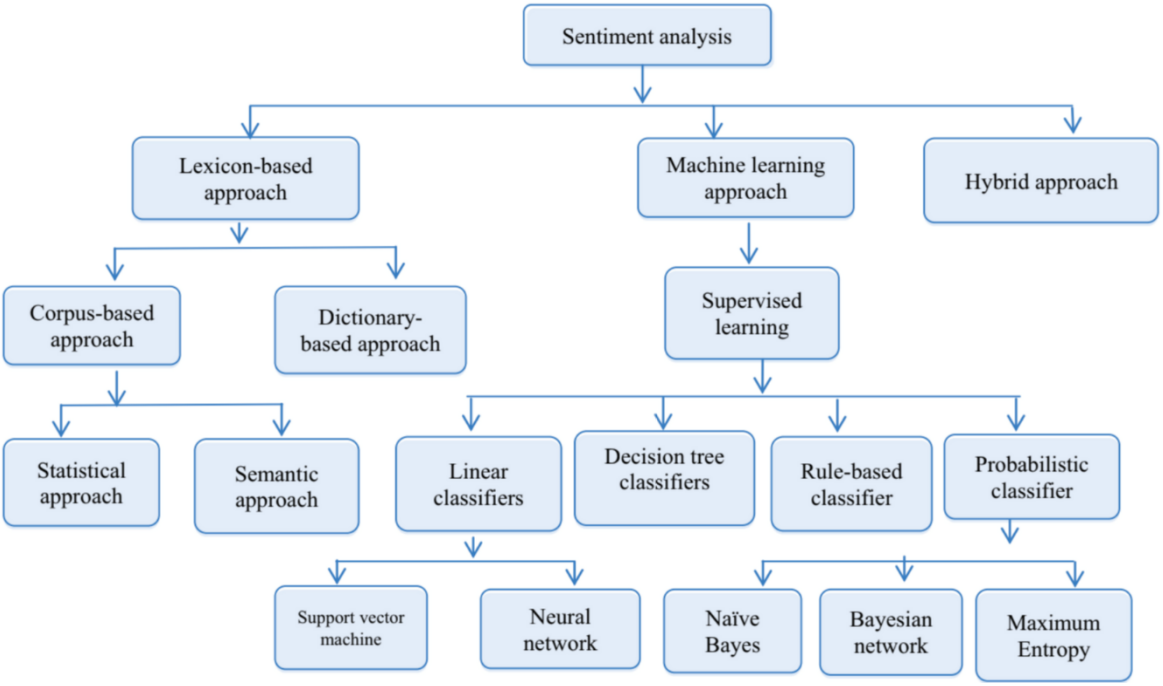

Figure 5. Classification Techniques of Sentiment Analysis [10]

The corpus-based approach also makes sense of the analysed words according to the general structure of the sentence, for example, classifies them as a whole according to conjunctions such as OR, BUT, AND in the sentence. Also, researchers clustered on the graph to determine whether they are positive or negative from the results obtained from the analysis of these sentences. [14] According to the Dictionary based approach, synonyms and antonyms are summed up and classified as positive and negative. [1]

Also, we test these approaches with their accuracy.

$$Accuracy = \frac{T}{N}$$

T: the correct samples number
N: the total samples number

6.1. Lexicon-Based Approach

Figure 6. Classification Techniques of Sentiment Analysis [11]

7. Comparison of Commonly Used Machine Learning Approaches for Sentiment Analysis

	Approaches				
	Rule-based system	**SVM**	**NB**	**ME**	**n-gram**
Advantages	Writing and implementing rules is easy.	1. High dimensional input space. 2. Document vectors are sparse.	1. Simple and intuitive technique. 2. It combines efficiency with reasonable accuracy.	This technique does not assume the independent features like NB technique.	Usage of 2-gram and more improve accuracy of SA instead of single word SA.
Disadvantages	It loses track when the data and scenario change faster than updates in rules.	1. More datasets are required in training phase. 2. Data collection is not easy.	1. Machine can be trained with less datasets. 2. It works with conditional independence between the linguistic features.	It is tedious.	1. n-gram dependencies can not be handled if n value is large. 2. Corpus data required to train machine.

SVM: Support vector machine; NB: Naïve Bayes; ME: Maximum entropy; SA: Sentiment analysis.

Table 1-Pros and Cons of Commonly Used Machine Learning Approaches for Sentiment Analysis

We compared the applications used in the sentiment analysis with previous articles. We examined and worked on peer-reviewed publications between 2010-2020.

In our first study, we examined the sentiment analysis studies that were made only in the Turkish language.

The studies are shown in Table 2. [31]

Authors	Methodology	Data	Indicators	Performance result
Erdogan et al. [16]	*n*-gram (1, 2, 3) method, logistic regression	2018	Five most used cryptocurrencies in English text tweets	94.60
Ciftci et al. [17]	RNN-based algorithm	2018	Turkish Wikipedia articles	83.30
Coban et al. [18]	BoW vs W2VC model	2013	Turkish Twitter messages in the telecom sector	59.17
Ecemış et al. [19]	Support vector machine	2018	Turkey-based geographical user data	0.954
Isik et al. [20]	Novel stacked ensemble method for sentiment analysis	2018	IMDB dataset including 1000 positive and 1000 negative; 2000 movie comments have been used	0.791
Karcioglu et al. [21]	Linear SVM and logistics regression	2019	Random English and Turkish texts have been collected by Twitter	65.62
Uslu et al. [22]	Logistics regression	2019	User reviews have been collected from Turkey's most preferred movie site	77.35
Kanmaz et al. [23]	Decision trees, support vector machine, and Naive Bayes methods	1996–2018	News text-related stock exchange	0.64–0.80
Doğan et al. [24]	LSTM recurrent neural networks	2019	In the study, a single mixed data pool with two categories is created with data collected from multiple social networks	0.9194–0.9266
Salur et al. [25]	Random forest classification method	2019	Tweets collected about special tourism centers	88.974
Santur [26]	Gated recurrent unit method	2019	Turkish e-commerce platform user reviews	0.955
Kamis et al. [27]	Multiple CNN's and LSTM network	2017	A corpus of different datasets is utilized based on three datasets used in SemEval (semantic assessment)	0.59
Ogul et al. [28]	Logistic regression classifier	2017	Public SemEval (semantic assessment) in three different sentiment analysis datasets containing both Turkish and English texts	79.56
Rumelli et al. [29]	*k*-nearest neighbor classifier	2019	The dataset is built by using e-commerce website (http://www.hepsiburada.com); the user review, rating, and URL of the product have been analyzed	73.8
Hayran et al. [30]	Support vector machine (SVM) classifier	2017	A Turkish text dataset classified (16000 positive and 16000 negative emotion) by emoji icon	80.05

Table 2-Sentiment Analysis Studies in Turkish Language

As can be seen in these tables, the study [16] performed with logistic regression methods with n-gram showed the highest performance result. The second higher performance result is the study [25] performed with the random forest classification method. The study which belongs third higher performance result is performed with Recurrent Neural Networks (RNN) -based algorithm. [17]

In our second study, we examined the sentiment analysis studies that were made in the English language. While doing our literature review, we learned that sentiment analysis not only examines product evaluation and people's emotional comments on social media but also doctors use this sentiment analysis to use it for the best treatments.

We made this Table-3 by considering the 2020 study of Sharma C, who has worked in the field of pharmacotherapy. These studies were carried out using the Lexicon-based approach and Machine Learning-Support Vector Machine Approach. [35]

Authors	*Title*, Journal and year	Data source and quality assessment (QA)	Type of SA and data pre-processing	Outcome of interest	Result	Significance
Cobb et [32]	*Sentiment Analysis to Determine the Impact of Online Messages on Smokers' Choices to Use Varenicline*, Journal of the National Cancer Institute Monographs. 2013	QuitNet QA not stated	LB (Salience Engine 4.1) Data pre-processing - No	Whether exposure to positive messages re: varenicline resulted in more people switching to it and sticking with it	Registrants who started or continued with varenicline were exposed to a statistically significantly greater number of positive-sentiment varenicline messages than negative-sentiment messages	While they cannot draw conclusions about causality, emotional content of online communications about health behavior intervention is associated with decision making around pharmaceutical choices
Korkontzelos et [33]	*Analysis of the effect of sentiment analysis on extracting adverse drug reactions from tweets and forum posts*, Journal of Biomedical informatics. 2016	DailyStrength forum and Twitter QA not stated	LB, 5 lexica used - the Hu&Liu Lexicon of Opinion Words (H&L), the Subjectivity Lexicon (SL), the NRC WordEmotion Association Lexicon (NRC), the NRC Hashtag Sentiment Lexicon (NRC#), and the Sentiment 140 Lexicon (S140) Data pre-processing - Yes	Whether the addition of sentiment analysis feature to ADRMine (a software already designed to pick up ADR mentions) would increase accuracy of picking up ADRs	There was an increase in pick up rate of ADRs for posts taken from twitter but not for posts from daily strength Of all the lexica used, Sentiment140 performed the best (lexica generated from twitter)	Thus, there is potential for sentiment analysis to be used to pick up ADRs
Ebrahimi et [34]	*Recognition of side effects as implicit-opinion words in drug reviews* Emerald Insight. 2016	www.drugratingz.com QA Not stated	ML using SVM and a Rule based version of lexicon based Data pre-processing - Yes	To evaluate if implicit sentiment can be used to identify drug side effects from disease symptom. These were tested against the manual annotation of the same drug reviews by a pharmacist	Experimental results show that ML outperforms the rule-based algorithm significantly for both disease symptom and especially side effect detection where it was almost two-fold better	The main finding was that drug review side effect recognition can be handled by using the ML algorithm, which significantly outperforms the regular expression-based algorithm

Table 3-Sentiment Analysis Studies 2020 Field of Pharmacotherapy

You can see the multi-linguistic sentiment analysis studies of the 2017 year in our third table. In these studies, the highest accuracy level was provided by the work with the Support Vector Machine (SVM), Naive Bayes, and K-Nearest Neighbours tools. [46]

Year	Ref. no.	Method	Target Language(s)	Dataset/ Domain	Major Contributions	Tools Used	Accuracy
2017	[36]	Deep learning model with parameter sharing and word embedding	Chinese, Japanese	Twitter data	Unifies parameter sharing and heterogenous word embedding methods in a deep learning model for a multilingual environment	CNN, FastText, Mecab, NLPIR, TweetTokenizer	57.3
	[37]	Deep learning with optimized convolution and character embedding	German, Portugese, Spanish	Twitter data	Uses character based embedding in deep learning models and eliminates the need of machine translation.	CNN, LSTM	66.0 – 69.7
	[38]	Convolutional n-gram Bi-LSTM word embedding	Italian	YouTube comments	Enhances word embedding by multiple convolutions, encodes long distance contextual dependencies.	LSTM	55.03 – 65.6
	[39]	Convolutional nets using n-gram	French, Greek	Restaurant reviews	Uses n-gram level information and works in a language independent manner, excludes code-switching and language translation	CNN	Precision : 0.84 – 0.93
	[40]	Deep CNN with character-level embedding	German, Portugese, Spanish	Twitter data	Language agnostic and translation free analysis depending on fewer parameters, reduces memory usage	CNN	69.7 – 77.0
	[41]	Bi-View CNN (BiVCNN)	Chinese	Book, movie, music reviews	Captures document-level cross-lingual relations in a parallel sentiment space, works on shared polarity between parallel texts	CNN, ICTCLAS, Word2Vec, Google Translate	80.16
	[42]	(a) Bi-LSTM Random Field classifier (b) aspect- based LSTM	Arabic	Hotel reviews	Employs (a) to extract aspect opinion target expression based on n-gram, finds polarity of extracted aspects using (b) using word and aspect embeddings	LSTM, Word2Vec, FastText, AdaGrad	(a) F1 score : 69.98 (b) Accuracy : 82.7
	[43]	Multi-layer CNN for weakly supervised sentiment classification	French, German, Italian	Twitter data	Uses three variants of multilayer CNN on sequences of word embeddings of weakly supervised data and doesn't require translation	CNN	F-measure: 0.63- 0.67
	[44]	Aspect Target Sequence Model (ATSM)	Chinese	Product reviews	Performs multi-grained aspect level sentiment analysis, learns intra-sentence context using word embeddings	LSTM, CNN	75.59 – 5.95
	[45]	Multilingual Sentiment Analysis via Text Summarization (MSATS)	Over 50 global languages	Product reviews	Performs text summarization to extract meaningful information, which is then utilized for polarity detection	SentiWordNet, kNN, SVM, NB, Bing translator	Precision : 0.86
	[46]	Multilingual emotion classification	Portugese, Spanish, French	News items	Evaluated effect of translation and language combination on emotion classification, applies stacking of monolingual classifiers	SVM, NB, Radial Basis Function (RBF), Google Translate	F- measure: 0.91-0.95

Table 4-Summary of Work Done on Multi-Lingual and Cross-Lingual Researches

7.Conclusion

As a result of this researches, we learned what sentiment analysis is, how sentiment classification is done, and what are various sentiment analysis approaches. We have examined the advantages and disadvantages of sentiment analysis approaches. Each has at least one pros and cons. We also compared the accuracy of sentiment analysis approaches against each other. When we look at the studies, the accuracy of the SVM tool is higher than machine learning in general. In addition, the accuracy of the studies using NB, K-NN, and CNN tools were found to be high. When we look at these results, we can consider using these methods in our project.

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8. Software Requirements Specification

9. Introduction

There are many comments made by individuals to evaluate a subject, product, or service on social media accounts. Organizations, manufacturers, or customers improve their services or products based on these comments. Customers can have an idea about the product or service by reading these reviews. During the purchasing phase, these comments are of great benefit to the users in the decision-making phase. Sometimes there are few reviews that can be read and evaluated by the client or the company. In some cases, these forums, polls, social media comments contain too many comments. At this point, sentiment analysis comes into play. These comments are categorized with various machine learning methods and classified as positive, negative, and neutral. Thanks to the Sentiment analysis, institutions, organizations, companies, and customers can make this analysis automatically and save time, and ensure correct inferences.

9.1. Purpose

We aim to determine the level of satisfaction of customers by analyzing the comments made by American airport passengers on the Twitter as a result of the service they receive. Using Python codes and machine learning algorithms, we will evaluate the service-taking comments of airport passengers and classify them as positive, negative, and neutral. By classifying the words such as "good, regret, amazing, bad, lovely, terrible" in the text, we will obtain results such as positive, negative, or neutral.

By analyzing the emotions of its passengers with sentiment analysis, it will guide American airports to improve or develop services by airport according to the results of this analysis.

9.2. Scope

In this project, we aim to analyze customer satisfaction based on the comments of American airport passengers. In this way, airport operators will evaluate customer satisfaction without having to read all the comments and direct their services accordingly. It is ensured that businesses can serve their service structure better with correct evaluation results. These evaluation results will be classified as positive, negative, and neutral, helping customers and airport operators make better decisions for their benefit. With this project, it is possible to develop services in the right direction for airports and to make better decisions for customers.

9.3. Glossary

Terminology	Definition
SRS	Software Requirements Specifications
NLP	Natural Language Processing
User	The person who wants to analyze emotions according to tweets written by passengers of American airlines.
Object	An entity that can be a product, service, individual, organization, event, or topic.
Attribute	An object has some attributes: delays, quality of service, etc.
Opinion	A person or organization that expresses a positive or negative sentiment on a particular attribute of an object at a certain time.
Opinion Holder	The person or organization that expresses the opinion.
Opinion Orientation	i.e., polarity, e.g., positive, negative or neutral.
Opinion Strength	Level, scale, intensity of opinion indicating how strong it is, e.g., contented, happy, joyous and ecstatic, whose strength are incremental.

9.4. References

[1] IEEE Std 830™-1998(R2009) Recommended Practice for Software Requirements Specifications.

9.5. Overview

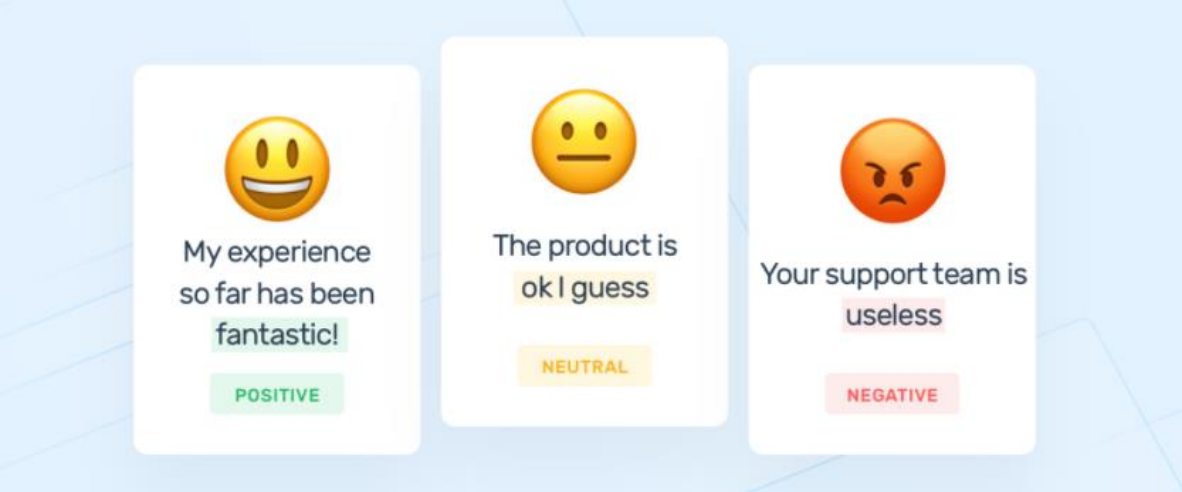
The continuation of this SRS document is as follows: In Section 2, the features of the project we will realize are mentioned for the users. Also, the limitations and risks of the project are detailed in this section. Chapter 3 discusses the requirements of the project we will realize using technical terms. Also in this section, the functions and features of this project are detailed for users. In Chapter 4, the use of the project we will develop is explained by visualizing it with diagrams.

10. Overall Description

In this section, various aspects of the project will be discussed.

10.1. Product Perspective

With sentiment analysis, it can be determined which way of thinking about a certain subject by evaluating people's comments depending on the comments or texts. In this project, the comments made by the American airport passengers about the service they receive on their Twitter accounts will be analyzed and classified. This project provides benefits such as providing a better service to its passengers by improving the services of the airport in line with the results of this analysis by making emotional analysis for the comments received from airport passengers.



10.2. User Characteristics

Sentiment analysis will be determined by opinion orientation according to the opinions expressed about some attributes of an object belonging to an opinion stated by the opinion holder. While doing this analysis, opinion strength is an important factor for a more accurate analysis. Our sentiment analysis is a process that automates the mining of opinions and emotions from comment tweets through NLP. Opinions are classified as positive, negative, and neutral with sentiment analysis. This project aims to analyze

people's feelings, attitudes, opinions, and feelings about the service and quality they receive from the American airport.

10.3. Constraints

Individuals' sensitivity to the service or the situation may be affected for different reasons. He can make a negative comment when he's having a bad day and about a topic he is neutral. With sufficiently large data, outliers can be diluted in these many interpretations to obtain more accurate results. It is also important to evaluate these interpretations in terms of time, as the mood of people may change over time according to the events that occur in the world. Context matters when it comes to mockery under the NPL. It is necessary to have a large sample of natural language data that provides clues to determine whether a statement a user uses is ironic or not.

10.4. Risks

The successful implementation of the project depends on careful examination and meeting of some risk conditions. These conditions for our project are listed below:

- Tweeter data should be collected.
- Tweets do not have a specific structure and free/colloquial language is used.
- A tweet may reflect satisfaction and/or dissatisfaction at the same time.

10.5. Assumptions and Dependencies

Emotion analysis for service comments is to obtain service characteristics and sensitivity based on the feature based on the assumption that these comment texts contain a hidden feature and emotional structure. In our project is assumed that sensitivity based on the context of the service feature can be captured by learning the corresponding features by word marking. Sentiment analysis suitable for the subject is based on controlled text classification, which can be used with decision trees and polarity

dictionaries, to determine the correct connection points for words containing polarity and to determine the relevant dependencies in each sentence in the comments.

11. Requirements

11.1. Specific Requirements

11.1.1. User Interface

There is no user interfaces for this project since there is no website or application will be developed.

11.1.2. Hardware Interface

Hardware interface is not needed for this project.

11.1.3. Software Interface

Twitter API will be used to analyse tweets in twitter. For high accuracy, we need big data so the system needs libraries such as Keras, Tensorflow.

11.1.4. Communication Interface

Communication interface is not needed for this project.

11.2. Functional Requirements

- Twitter data should be collected
- System should be able to process new tweets stored in twitter's database.
- System should be able to analyze data and classify tweets' polarity

11.3. Non-Functional Requirements

Non-functional requirements require the following:

- It should use big dataset for high accuracy
- Tweets do not have a specific structure and free/colloquial language is used
- It should be user friendly.
- It should provide efficient analysis process in very large data in a short time.
- It should provide the high accuracy and most reliable feedback.

11.4. Software System Attributes

The system need to Windows 7 or higher operating system. Also, the system requires Text Editor,

8GB or more RAM and 2.5 GHz or more speed is needed for this project.

11.4.1. Reliability

We will safely shoot our target through the Twitter API.

11.4.2. Avaibility

We will work with big data to ensure high efficiency. We will make use of Keras, Tensorflow open libraries for this.

11.4.3. Performance

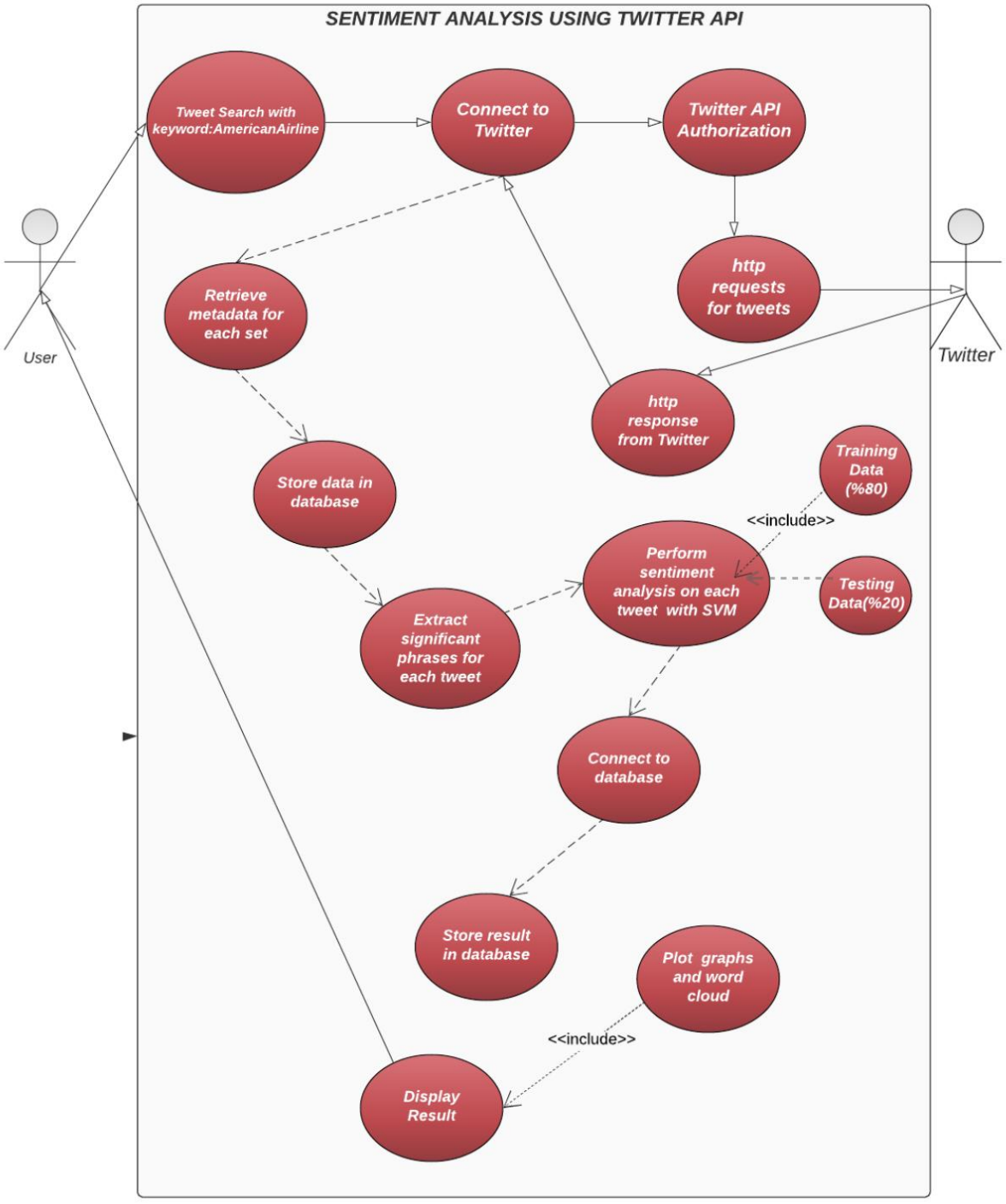
It should provide the high accuracy and most reliable feedback.

11.4.4. Portability

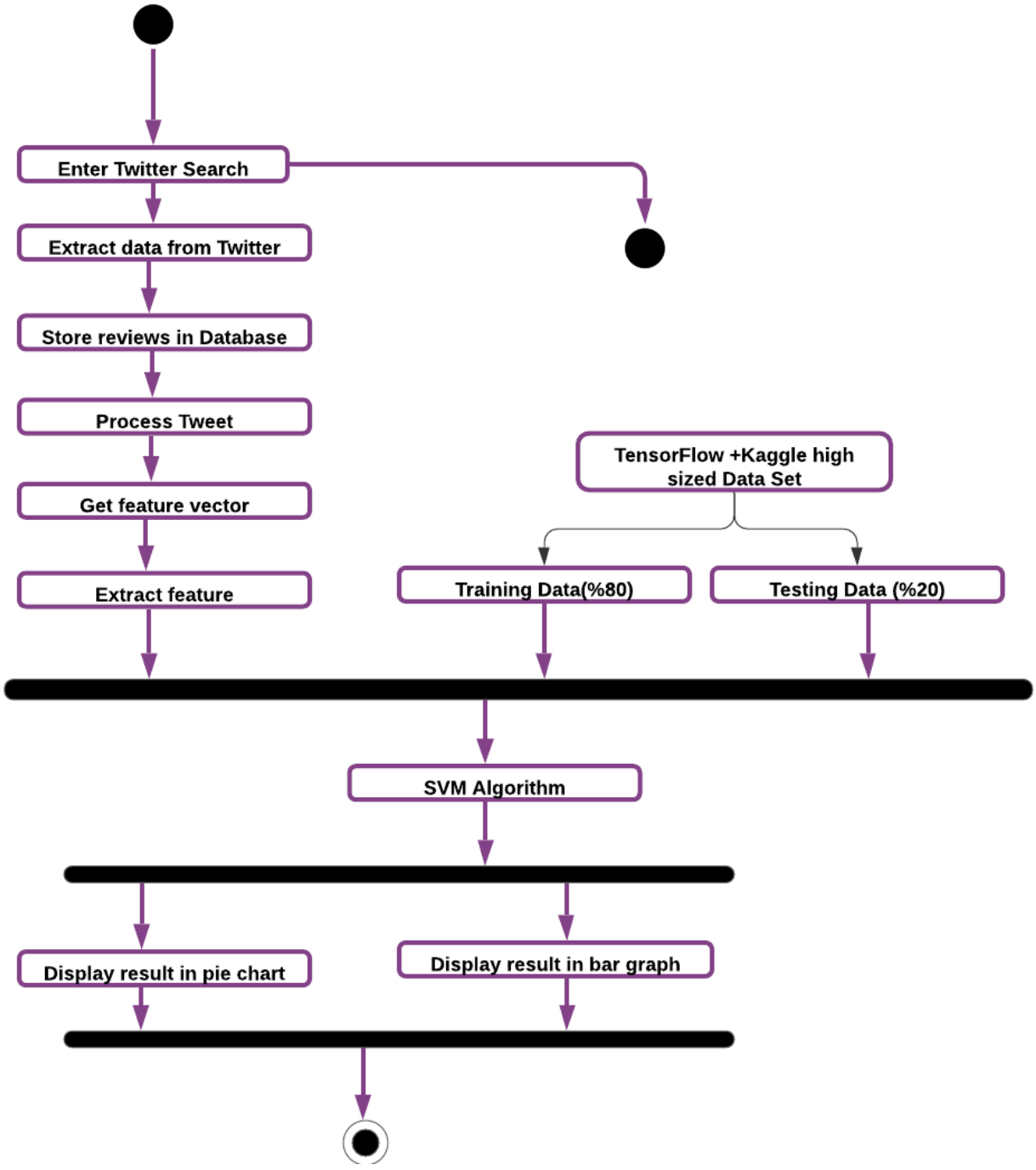
The system will be useful in both Linux and Windows.

11.5. UML Analysis Model

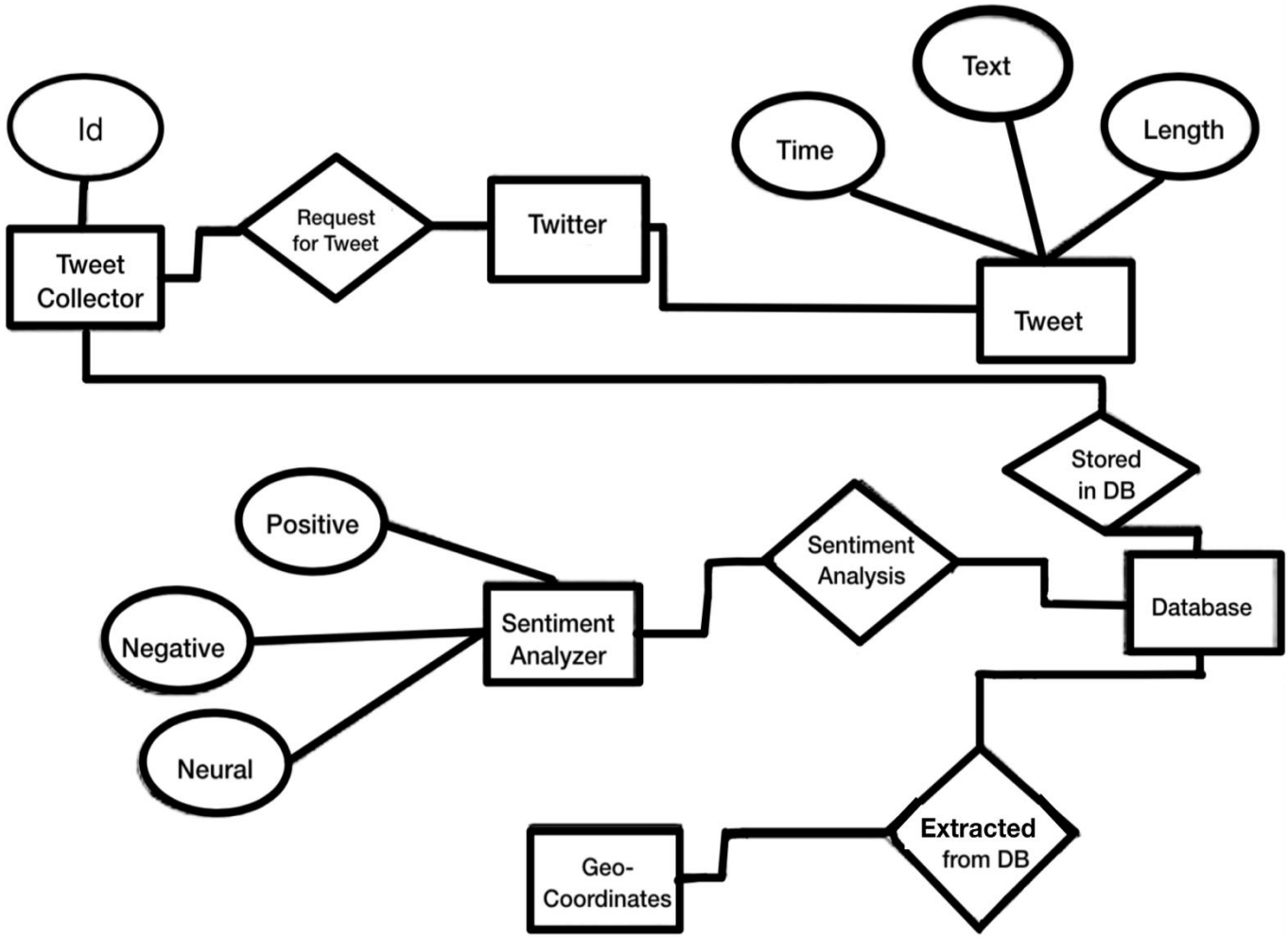
11.5.1. User Case Diagram



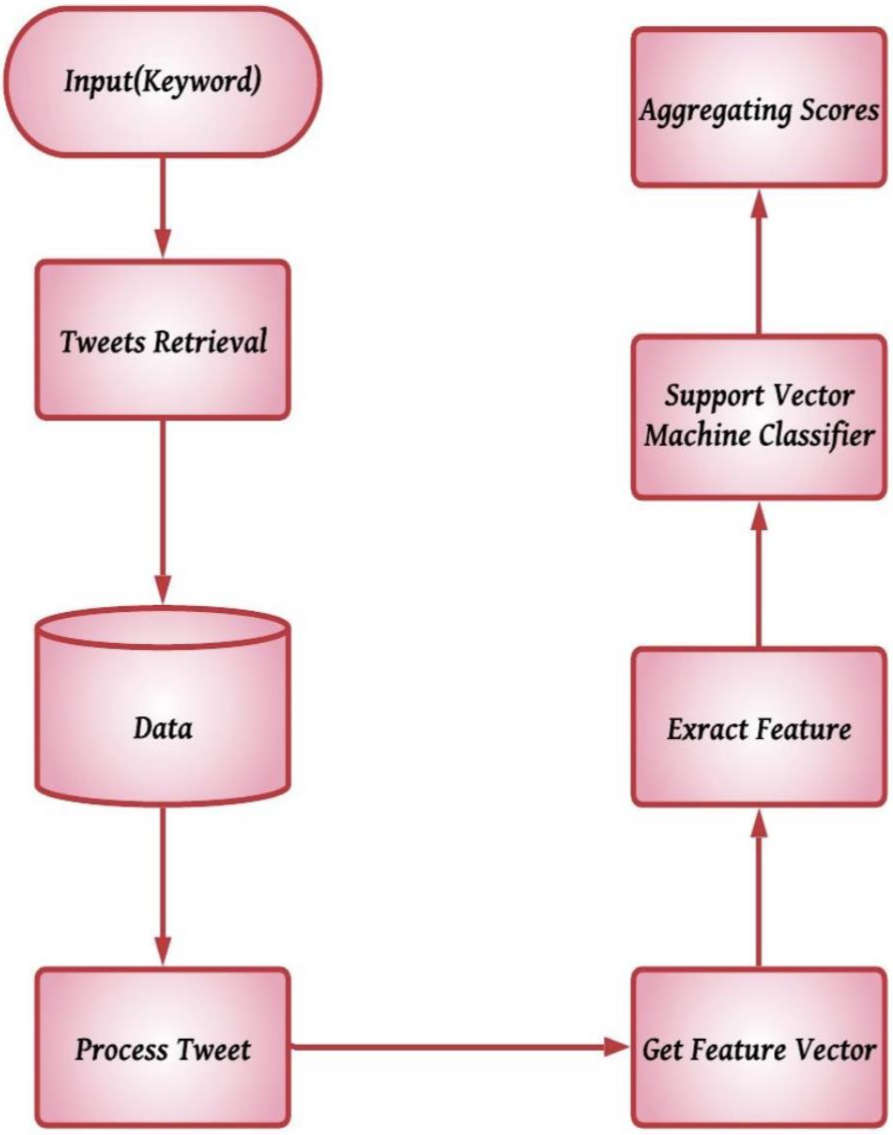
11.5.2. Activity Diagram



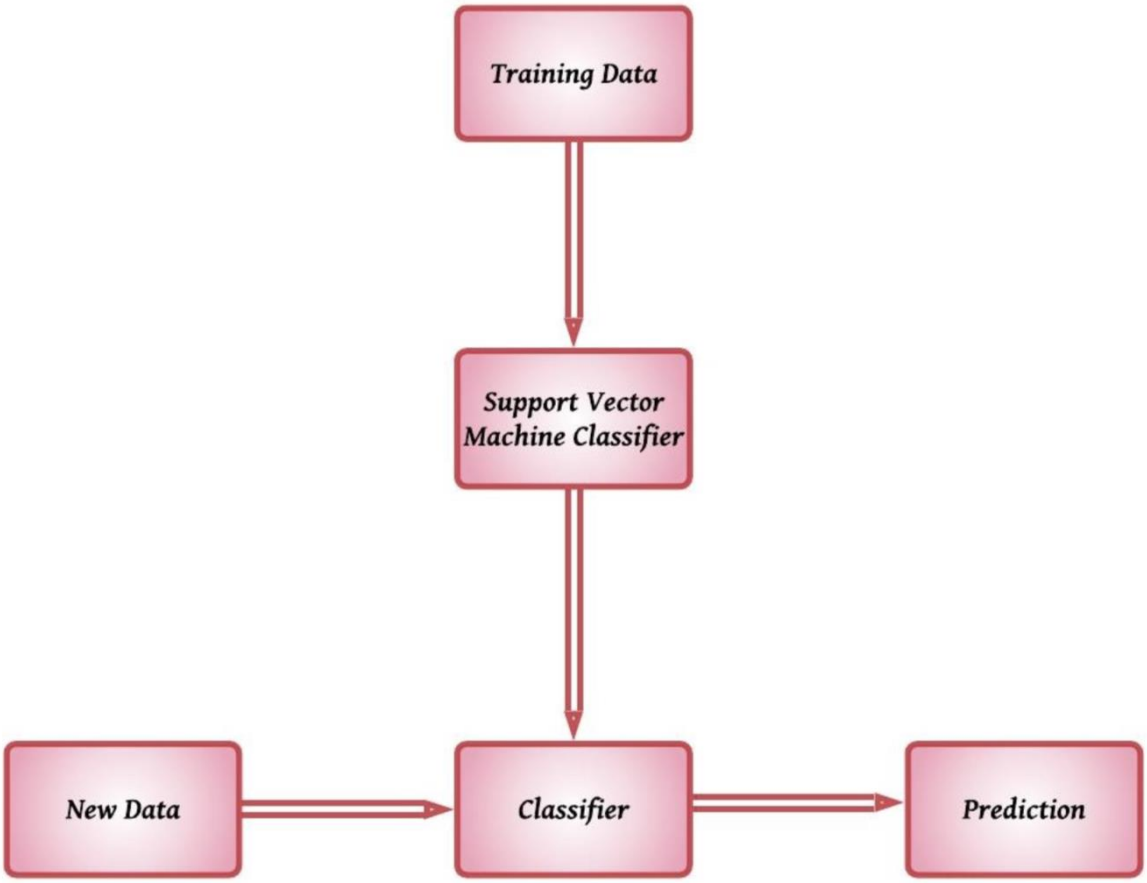
11.5.3. ER Diagram



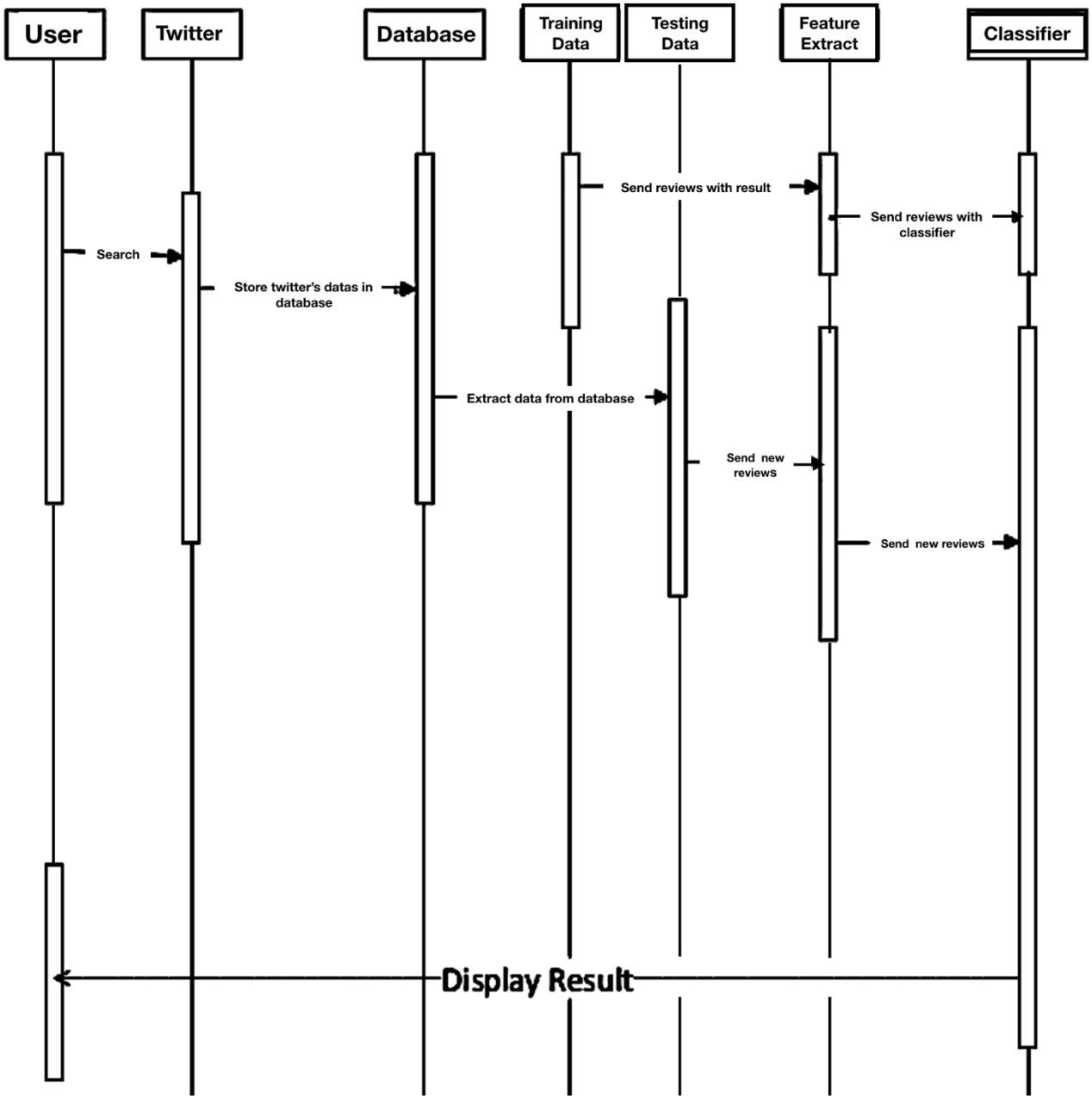
11.5.4. Data Flow Diagram



11.5.5. System Flow Diagram



11.5.6. Sequence Diagram



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13. Software Design Description

14. Introduction

14.1. Purpose

The purpose of this SDD is to describe the project that analyzes the comments made by the airport passengers on Twitter. This project aims to classify the comments made by the passengers on Twitter to evaluate the quality of the service that the American airport provides to its passengers and to conduct an emotional analysis. In this project, it is aimed to measure the satisfaction level of airport passengers based on the comments they make on Twitter to evaluate the service they receive. This project allows American airports to provide a better service to their passengers by improving the service they provide according to the results of this analysis.

14.2. Scope

This project will be very beneficial for airport companies. It will be boring for airports to read the comments made by airport passengers one by one and determine the satisfaction level of the passengers. In this project, we will use machine learning methods to classify the comments made by the passengers about the service they receive and conduct sentiment analysis. According to the comments of the passengers, we will classify their emotions as positive, negative, and neutral, and we will facilitate the work of airport operators by determining the general level of satisfaction. We need a lot of data for accurate analysis. We are considering extracting data from the Kaggle platform to satisfy our data needs. We intend to use SVM classifier algorithms, whose classifications yielded better results than the inferences we made from previous studies. We will use the SVM classifier, a controlled machine learning algorithm that can be used for classification or regression problems in our project. SVM training algorithm works by creating a model that assigns new examples to these categories by transforming it into a linear classifier when a series of training examples marked in different categories are given. SVM is an algorithm that is actively used and preferred in many machine learning projects. The biggest reason we chose it is that it has given better results in previous studies on this subject.

14.3. Glossary

Terminology	Definition
SDD	Software Design Document
SVM	Support Vector Machine
Diagram	Symbolic representation of information using visualization techniques.
Sentiment	A view or opinion that is held or expressed.

14.4. Overview of Document

The contents of the chapters that follow this document as listed below:

Chapter 2 has been prepared with diagrams and explanations to provide an overview of the work we will do, the functioning of the project and the path to be followed.

In the last chapter, in Chapter 3, the implementation of sentiment analysis process classification algorithms is mentioned.

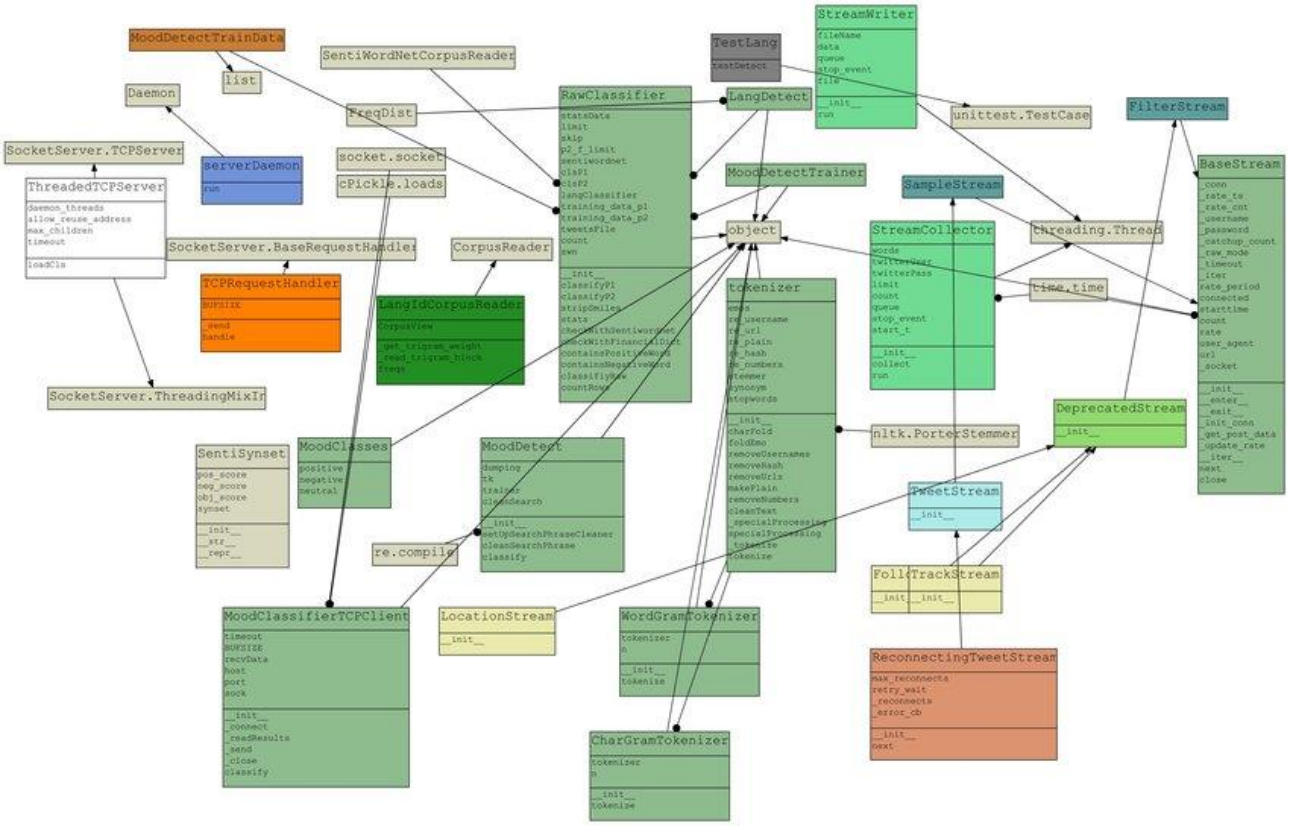
14.5. Motivation

We are senior students of the computer engineering department. We like to work on artificial intelligence and machine learning. For this reason, we chose this subject as our project topic. We are students who enjoy researching, improving ourselves, and learning new things. We wanted to improve ourselves more in the field we love by choosing a project topic that belongs to our field of interest. Our most important source of motivation is that this project will benefit airport companies by facilitating their work.

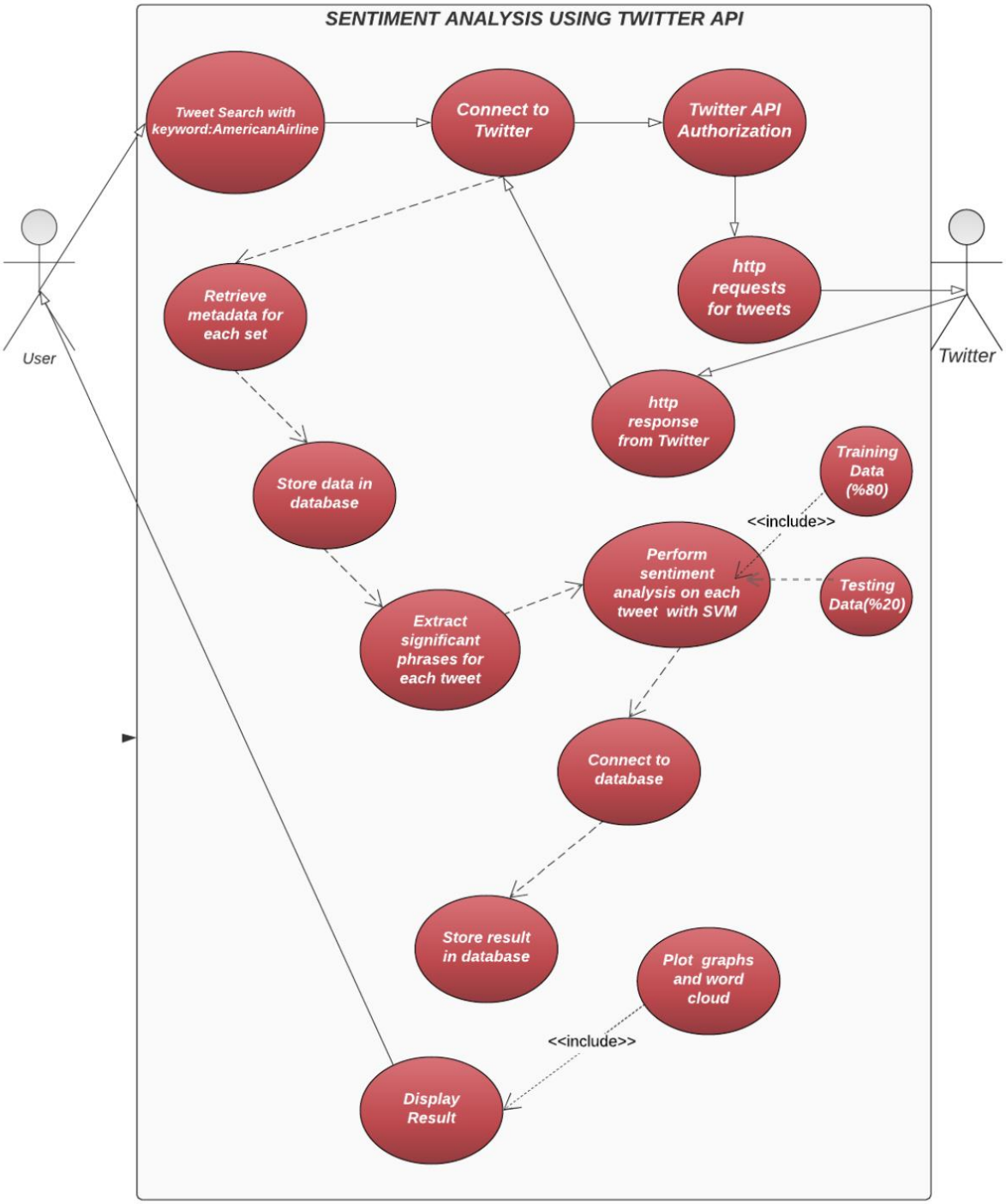
15. Design Overview

In this part, we give lots of details for our project. We explain all diagrams step by step.

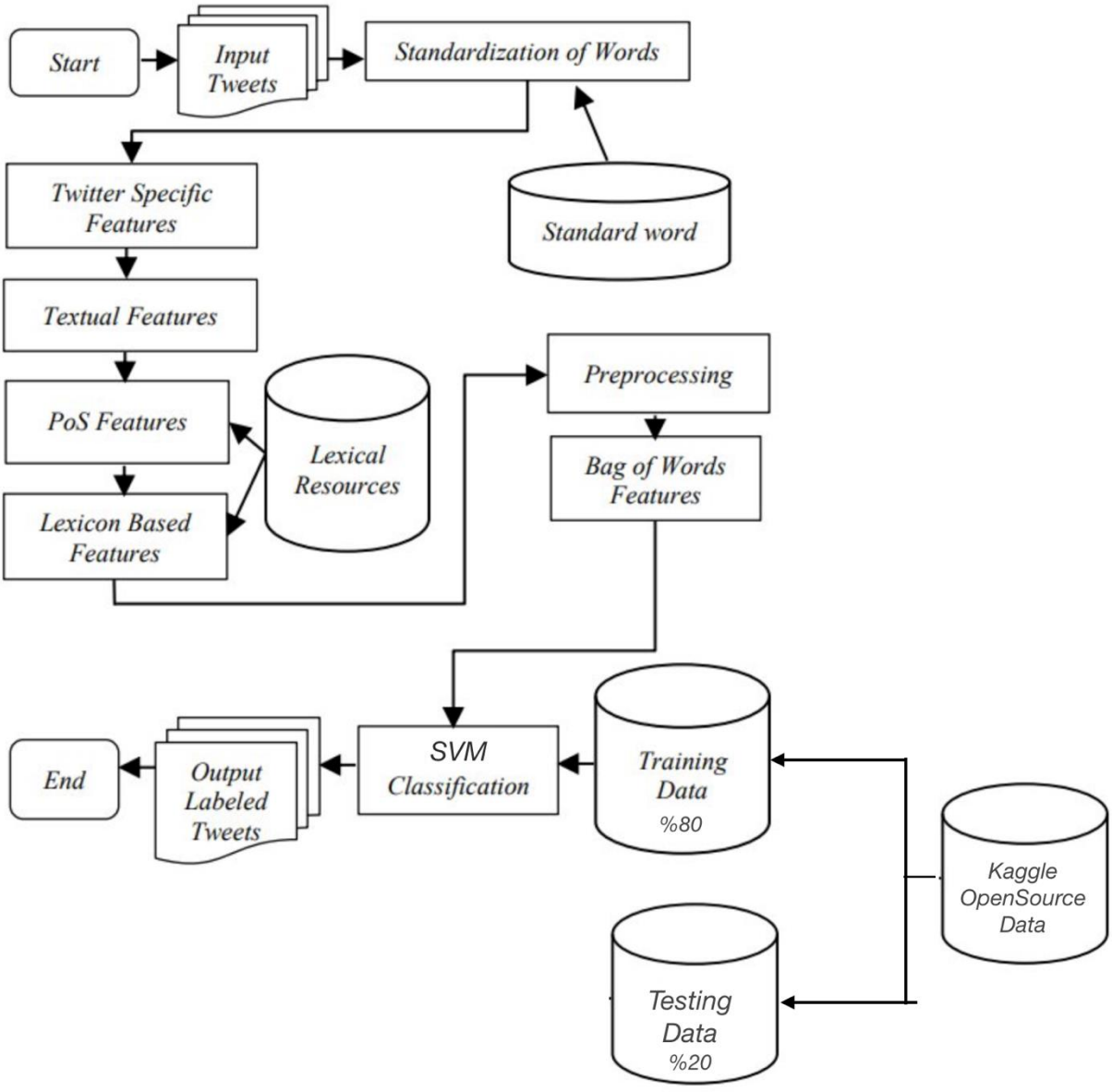
15.1. Class Diagram:



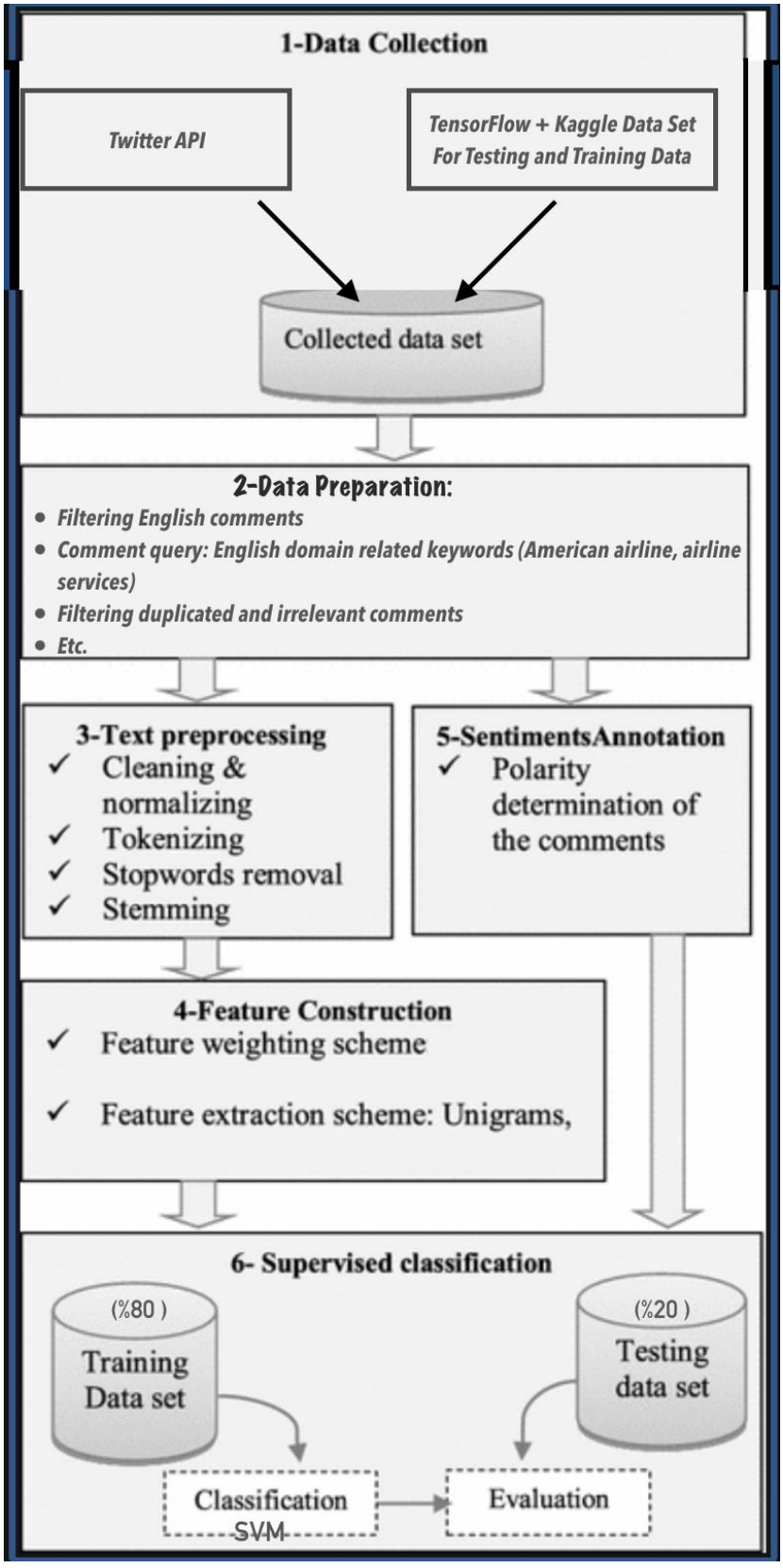
15.2. Use Case Diagram:



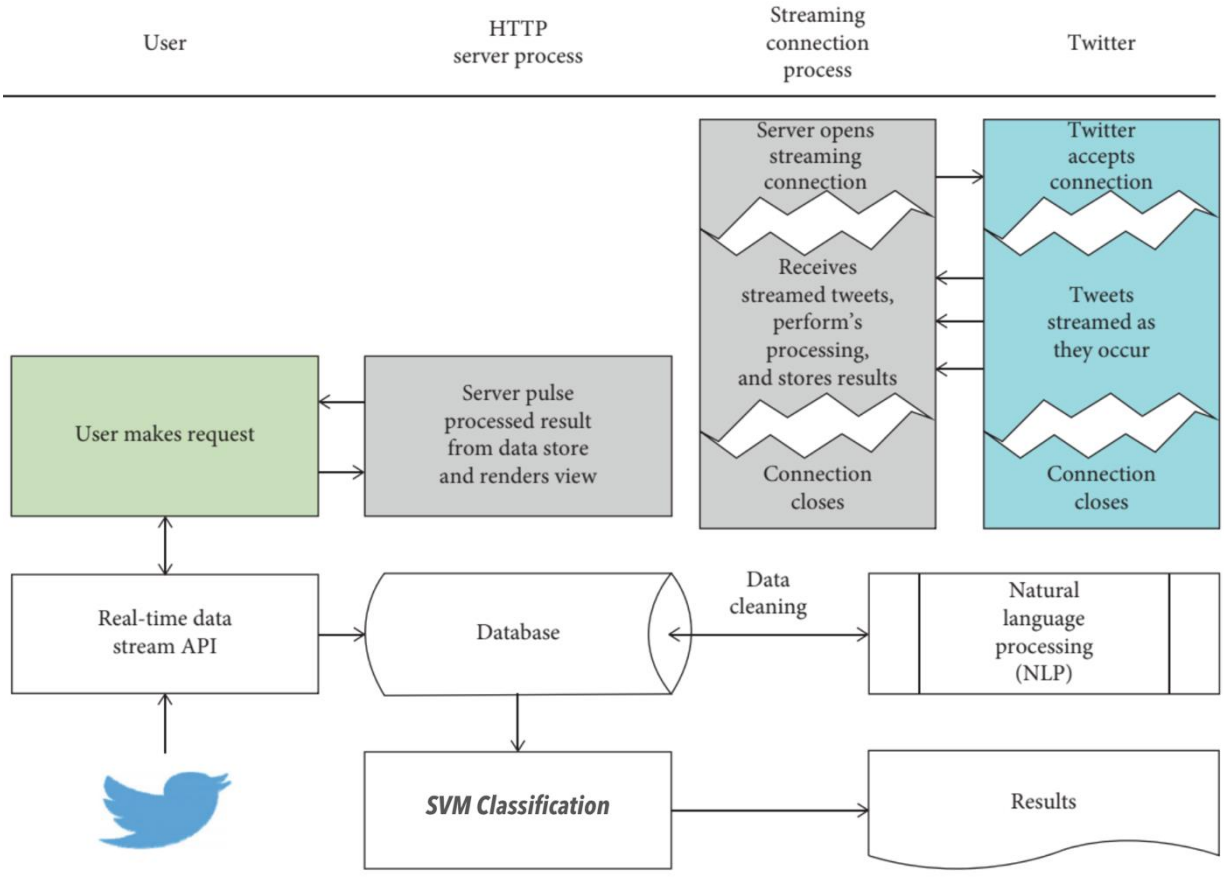
15.3. System Flow Diagram:



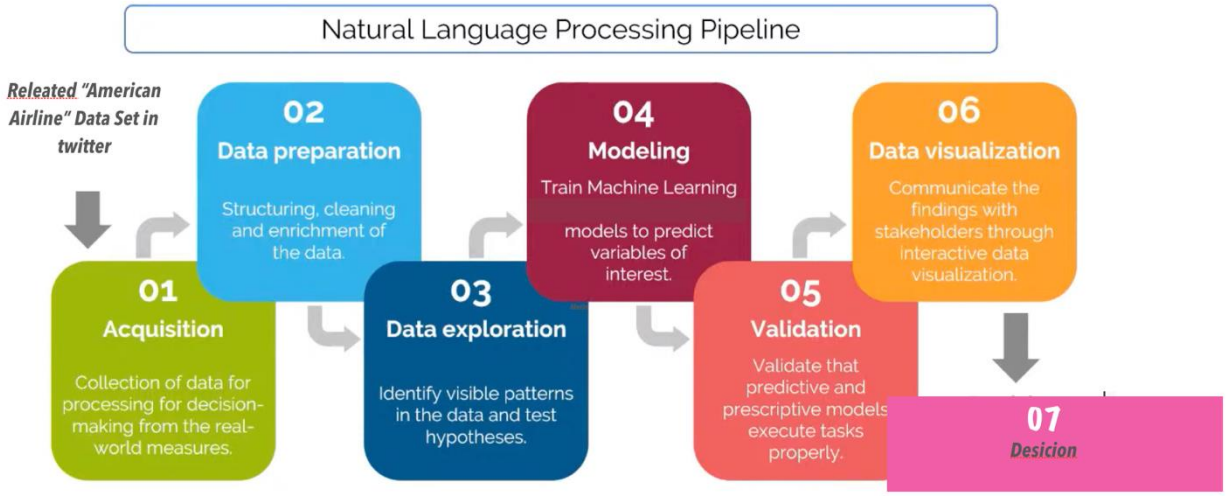
15.4. Time Series Processing of System:



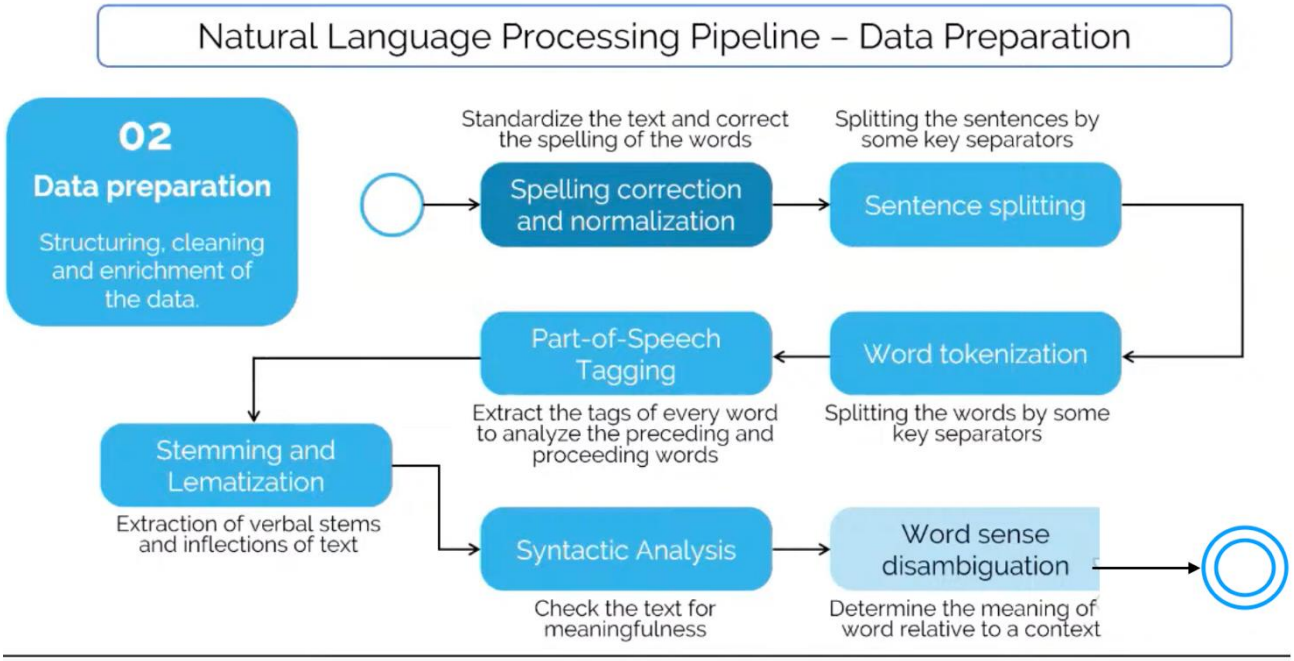
15.5. Data Collection Process via Twitter:



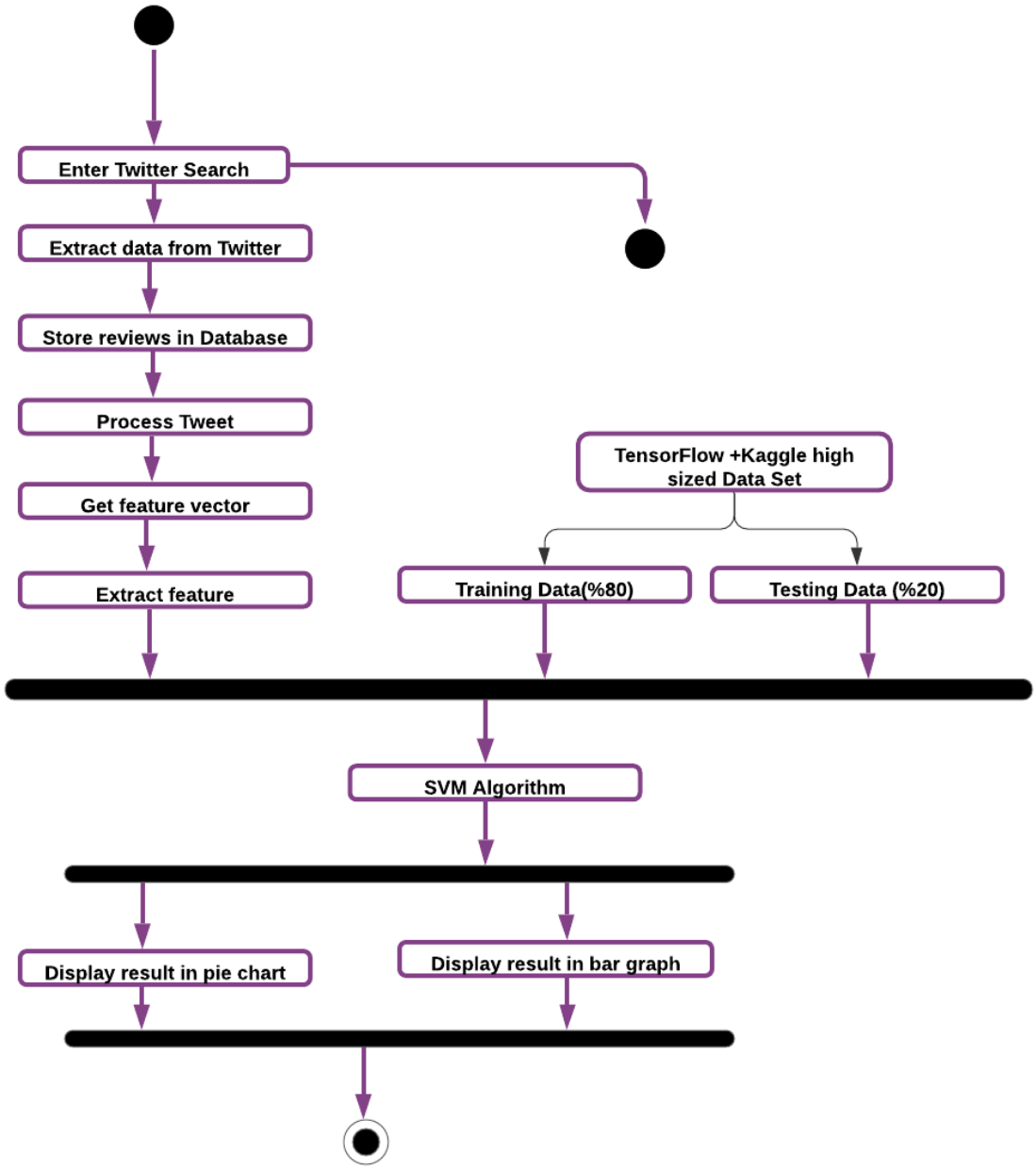
15.6. General Natural Language Processing Perspective:



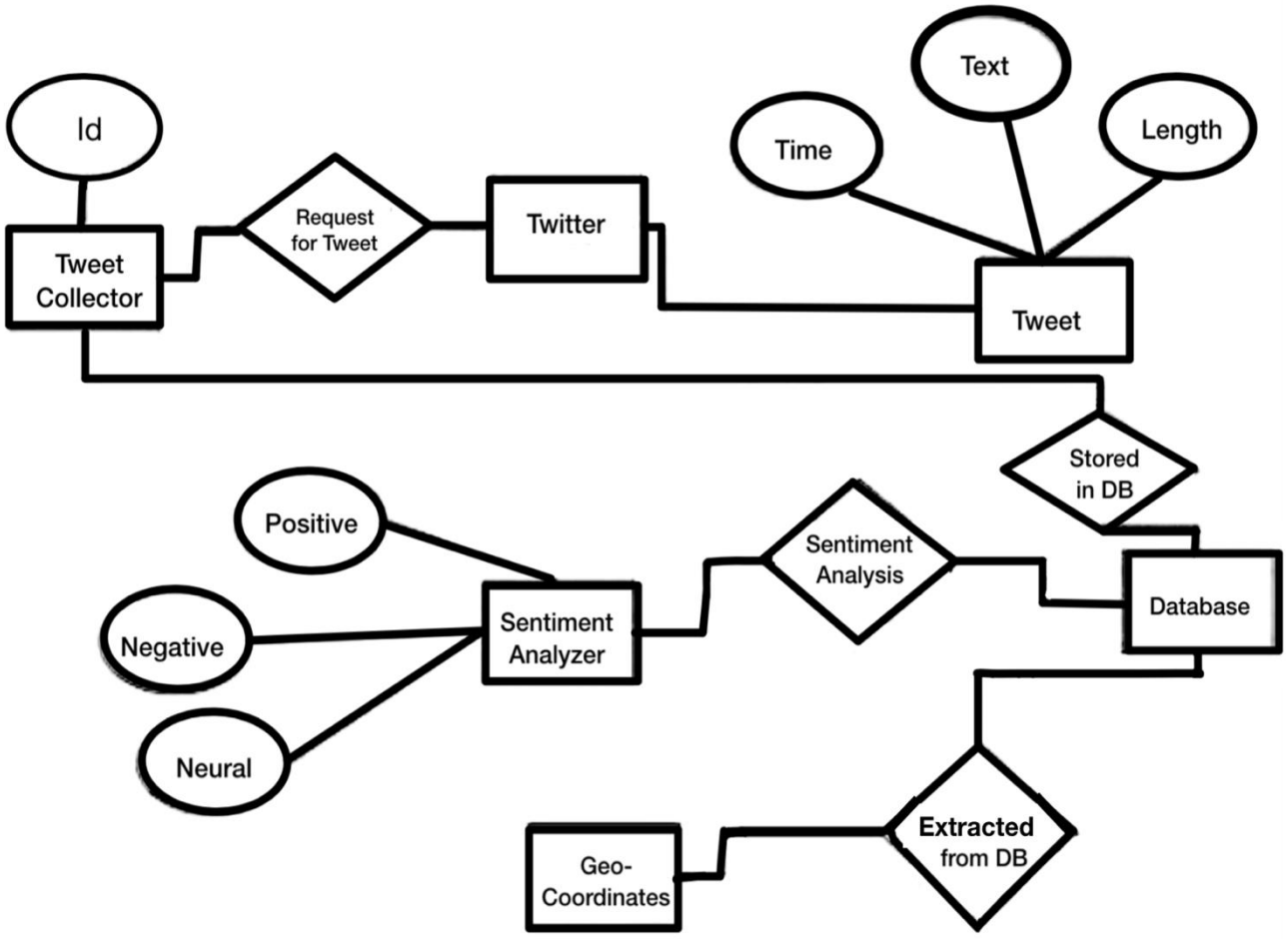
15.7. Text Preprocessing:



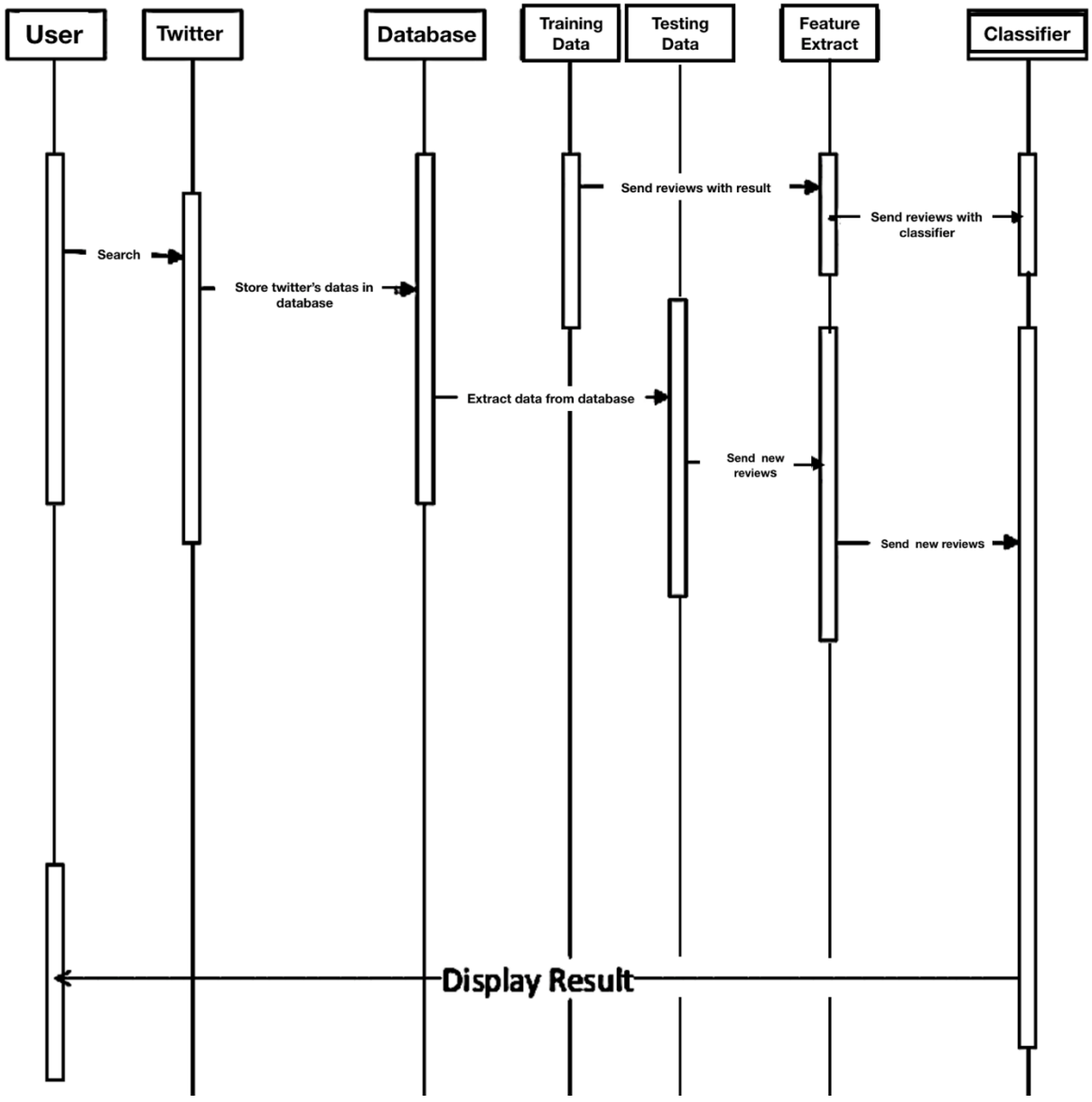
15.8. Activity Diagram:



15.9. ER Diagram:



15.10. Sequence Diagram:



16. Detection

In this project, the comments made by users as a text input on Twitter are classified using machine learning methods. Twitter comments made by the airport passengers as text input are divided into smaller meaningful units by tokenization. After tokenization, words of unnecessary frequently used words, that is, stop words, should be filtered. With negation handling, negative words and their combinations with positive or negative words are recognized. Word roots are found with stemming. Then the comments are divided into classes using the classification methods. We will use the SVM classifier for classification. In this way, we will do sentiment analysis for airport passengers by following a route.

17. References:

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