MACHINE LEARNING BASED MULTI-SCALE SENTIMENT ANALYSIS FOR AFAAN OROMO POSTS

M.Sc. THESIS

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We here by certify that we have read and evaluated this Thesis entitled **“Machine Learning Based Multi-Scale Sentiment Analysis for Afaan Oromo Posts”** prepared under our guidance by **Tadesse Kebede**. We recommend that it be submitted as fulfilling the thesis requirement

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DEDICATION

This thesis is dedicated to my father *Obbo Kabbadaa Guuggee (Baabba)* and my mother *Aadde Kabbabush Balaay (Aayyoo*).

Aayyoo ati guyyaa ana deesse irraa eegaltee amma ani hanga kanaa gahutti tolchitee waxxee na guddifte, ofii dadhabdee naaf mijeessite, na jaallatte, na jajjabeessite, na gorsite, naaf yaadde. Jecha kee keessaa kan ani hin hirraanfanne*"Fayyaa keessan tahaa ijoollee koo inni guddaan kana nun jetta".* Ati arjoomtuu dha, ollaa kan nyaachistu, namaaf kan yaaddu, kan waaqayyoon sodaattu galatoomi *Aayyoo* koo. Hojiin kun bu'aa dhamaatii keeti, sin jaalla dha, naaf jiraa dhu. *Baabba* ati tokkicha kooti "*Tokkicha amma dhibbaa*". Na gorsita, na taphachiifta, na barsiifta, naaf rakkatta. *Baabba* dubbiin ati dubbattu barnoota qaba, egeree jireenyaas fooyyessa. Jechamoota kee kana keessa kanaan hin daganne, *"Hojiin kee sumaan nyaata sumaan baasa", "Ani isa fulduraa malee isa darbe hin argu", "Afaan namaa baruun guddachuu dha"* kanneen jedhan baayyee na barsiisan. Yoo nu gorsitu *"Narra dhaabbadhaati isiin iddoo guddaa gahaa jetta".* Galatoomi *Baabba*. Naa jiraa dhu. Carraa kanaan fayyadamee hojiin kun bu'aa dafqa kee akka tahe sittan hima.

STATEMENT OF THE AUTHOR

By my signature below, I declare and affirm that this Thesis is my own work. I have followed all ethical and technical principles of scholarship in the preparation, data collection, data analysis and compilation of this Thesis. Any scholarly matter that is included in the Thesis has been given recognition through citation.

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BIOGRAPHICAL SKETCH

Tadesse Kebede is an instructor in Haramaya University, Haramaya, Ethiopia. Tadesse Kebede was born on February 06, 1993 GC, in Ethiopia, Oromia regional state, Horro Guduru Wollega, Amuru, Agamsa. He attended his primary education at *Agamsa Primary School,* his secondary school education at *Agamsa Secondary School* and his senior secondary school education at *Amuru Preparatory School.* He graduated from Mekelle University with degree of Bacheler of Science in Computer Science in July 2016. After receiving his degree, in 2017, he joined Departemt of Computer Science, College of Computing and Informatics, Haramaya University as instructor by position of graduate assistance two (GA-II). He worked there for one year, and in 2018, he started to study masters in Computer Science at Haramaya University Post Graduate in a regular program. Tadesse Kebede came with academic research work for masters in Computer Science in October 2019.

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ACRONYMS AND ABBREVATIONS

AI	Artificial Intelligence
BBC	British Broadcasting Corporation
BOW	Bag-Of-Words
DSR	Design Science Research
FN	False Negative
FP	False Positive
IDLE	Integrated DeveLopment Environment
LSA	Latent Semantic Analysis
MaxEnt	Maximum Entropy
NB	Naïve Bayes
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
OBN	Oromia Broadcasting Network
OMN	Oromia Media Network
POS	Part Of Speech
RQ	Research Question
SVD	Singular value decomposition
SVM	Support Vector Machine
TN	True Negative
TP	True Positive
VOA	Voice of America
WPR	World Population Review

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ABSTRACT

In daily decision-making activities, individuals or organizations regularly take other people's sentiments or opinions as one source of information. To be more precise about the opinion of the people, it is crucial to consider the strength of polarity of the sentiments. Nowadays the proliferation of the internet as websites, blogs, social networks, online portals and content sharing services contributes enormous amount of user generated Afaan Oromo texts. Even though the rising usage of Afaan Oromo language on the internet, there is no sufficient sentiment assortment and cataloging method for the language. Therefore, the multi-scale sentiment analysis task which enable to automatically extract sentiments by considering strangeness of sentiment in account are indeed desirable in various applications. This work can play significant role in sustaining these desires. In this study, multi-scale sentiment analysis model for Afaan Oromo text is proposed by using bag-of-words feature representation with three supervised machine-learning algorithms: Naïve Bayes (NB), Support Vector Machine (SVM), and Maximum Entropy (MaxEnt). The Afaan Oromo multi-scale sentiment analysis process involves categorizing a sentence into five predefined classes such as strong positive (+2), strong negative (-2), positive (+1), negative (-1) and neutral (0). The proposed system contains different components like data collection, preprocessing (tokenization, normalization, stop word removal), morphological analysis (part of speech tagging, stemming), sentiment annotation, feature extraction/selection, training a machine learning algorithms, classification and evaluation of the result using evaluation metrics such as accuracy, precision, recall and f-measure. For conducting the exiperiments 1000 Afaan Oromo sentences with sentiment are collected from different sources. In addition to this, 350 stop word lists, 254 suffixs, 740 gazetteers of Afaan Oromo adjectives and 125 intensifiers (adverbs) are prepared with the assistance of Afaan Oromo language experts. The experimental results shows that performance of the system model is encouraging achieving accuracy of 74.6% for NB classifier using 1000 sentences, and using 1200 sentences the system achieved accuracy of 83% for SVM classifier. However, further research work such as named entity recognition, word position and negation features, explicit and comparative sentiment analysis, standard corpus preparation, co-reference resolution and feature or aspect level sentiment analysis are needed to develop a full-fledged and a more efficient multi-scale sentiment analysis for Afaan Oromo.

Keywords: Multi-Scale, Sentiment, Sentiment Analysis, Posts, Intensifier Words, Bag-Of-Words, Machine Learning, Classification, Prediction.

1. INTRODUCTION

1.1. Background of the Study

The recent proliferation of the internet as websites, blogs, social networks, online portals and content sharing services contributes enormous amount of user generated sentiment texts such as beliefs, recommendations, ratings, reviews, discussions, news, comments, feedbacks, places or personalities, knowledge's, evaluations, values, attitudes, emotions or feeling about services, products, peoples, events, health, education etc. This increased sentiment information used by governments, marketers and companies to understand how the crowd thinks. In making decision in our day-to-day activities, we regularly take care of other people's opinions. The political parties ask to get opinion of people when forming a political vote, people may hear the consumers view when they buy appliances, friends ask each other to indorse good cinema, restaurant, jewelry, supermarket etc. So in order to put on hand these decisions, techniques that used to process the degree of peoples sentiment is a serious issue. Therefore, the multi-scale sentiment analysis fields, which enable to automatically extract many sentiments by considering intensity of sentiment in account and examine sentiment from those texts, are indeed desirable in various applications.

As individual's sentiment is the key feedback for governmental and non-governmental organizations, it has to be mined in short period and with a minimum effort. Pang and Lee (2008) referred sentiment analysis as subjectivity analysis, opinion mining, and appraisal extraction, with some connections to affective computing (computer recognition and expression of emotion). In this paper, the name sentiment analysis interchangeably used with the name opinion mining.

Sentiment analysis or opinion mining is an interdisciplinary theme that exploits methods from natural language processing (NLP), text mining and computational linguistics to recognize and extract subjective information from source materials (Khan *et al*., 2009). It includes grouping of data in a class or set of their polarity depending on the aspects of the people's opinion. To list some polarity may be positive, negative or neutral. Neutral often implies no opinion. The sentiment analysis regularly considers subjective elements, defined by Wiebe *et al*. (2004) as "linguistic expressons of private states in context". These elements are usually single word, phrase/sentence which designates that the sentiment exist in on small linguistic elements. According to Padmaja and Fatima (2013), generally sentiment analysis has been investigated mainly at three levels document level, sentence level and aspect or feature level. Document level sentiment classification categorize whether total opinion document expresses a positive or negative sentiment (Pang *et al.*, 2002; Turney, 2002). For example, given a single entity or object appraisal, the document level sentiment analysis decides total positivity or negativity of the entity appraisal. This is not usable for the document that estimate and contrast multiple entities because it only assumes that each document states sentiments on single topic (e.g., a single person or product).

The sentence level extracts the opinionated terms from the sentence and classify them to either a positive, negative, or neutral sentiment. It counts the number of the opinionated words in the sentence, depending on sentiment size the sentiment classified in to the polarity levels. Sentiment analysis at this level is about subjectivity classification(Wiebe *et al*.,1999), includes objective sentences which prompt factual information of the sentence and subjective sentences which express particular opinions and sentiments.

Hu and Liu (2004) refers aspect level sentiment analysis as feature level (feature-based opinion mining and summarization). It discover both the opinion and target of opinion on entities and/or their aspects and then summary of opinions are made. Even though the sentence is positive, we cannot say whole sentence is positive. For example,"*Hootelli Raas baayyee namatti tollullee sireen isaa garuu mijataa miti*" ("although the bed room is not comfortable, Ras Hotel is very interesting"). In fact, the sentence is positive about the Hotel but negative about the beds (entity) of the hotel. The level needs co-referential concept of the sentence so that it is more difficult.

In order to classify texts into their sentiment class two approaches of classification are there (Pang *et al*., 2002); machine learning approach and lexicon based approach. Machine learning necessitates forming a model by training a classifier with labeled samples. There are predominantly two types of machine learning practices, supervised learning and unsupervised learning. In Supervised learning, a collection of sentiment trained with labelled examples and labels provided to the model to decide the polarity. In contrasting of supervised learning unsupervised is unlabeled and they do not offer with the correct aims at all and therefore depend on clustering. The second sentiment analysis method, lexicon based approach uses dictionaries of words footnoted with their semantic orientations. It has two techniques dictionary-based approach, and corpus-based approach (Bird *et al*., 2004).

Corpus-based approaches find co-occurrence patterns of words to determine the sentiments of words or phrases (Hatzivassiloglou and Wiebe, 2000, Turney, 2002). Dictionary- based approaches use synonyms and antonyms in WordNet to determine word sentiments based on a set of seed opinion words (Fellbaum, 1998).

Sentiment analysis is used by the sectors such as advertisers, movie creators, book sellers, political parties, supermarkets, industries, restaurants etc. that demand their customers' feedback on a particular issue to improve themselves afterward. For example, (1), sentiment analysis used in government election to examine the people's sentiments, appraisals, attitudes, and emotions on the candidates of the election. (2), business company introduce new product to the market and then usefully extract the sentiment of the people on internet about product, and settle the future feasibility of this new product. It is possible to gather the sentiment from customer using surveys, blogs and suggestion committees but this may result in wastage of resource and not provide us the comment in a short period. Automatically gathering and classifying the sentiment that expressed by natural language on the social networks eradicate those problems with a minimum time and resource.

The goal of this thesis paper is to perform a multi-scale sentiment analysis of Afaan Oromo posts using python programming language and adopting supervised machine learning method. To do multi scale sentiment analysis the research performs tasks such as, preprocessing the language sentiment texts, morphological analysis, feature extraction, training the machine by labeling sample data and classifying the opinion into one of the polarity classes' using machine learning based classifier with bag-of-words (BOW) feature representation model. For sentiment classification five sentiment classes have been applied, +2 and +1 for the extent of more positive and less positive respectively, in other way -2 and -1 for the extent of more negative and less negative and for the neutral sentiment 0 polarity have been is used. Finally, the result generate using the classified sentiment and the accuracy have been measured using accuracy, precision, recall and f-measure, and the result is evaluated in terms of models.

1.2. Statement of the Problem

Getting sentiment of people on the business sector organizations engaged in leads to success in the field/business. Because of the recent technological advancement, many peoples from Ethiopia, specifically Oromo people, which covers 34.4% (WPR, 2018) of the country, post their feelings on issues such as politics, products, services of the organization, individual peoples etc. on social media. By considering this, it is an appealing challenge to find the optimal way of gathering the opinion individuals have for either of these issues.

Currently, opinion of the peoples towards governmental and non-governmental organization in Oromia region are gathered by holding different conference/meetings within the country and by using the oral and manual collection methods. Such ways of collecting peoples view greatly consume time and resource. In order to optimize this trend, one has to identify what people are interacting with in their day-to-day life that allows grasping the full sentiments regarding some issues in a little time and with optimal resource. Nowadays, the internet technology that are invented in the world like Facebook, Twitter, Blogs, Websites etc. are usable in using Afaan Oromo language easily as it uses Latin Script for Writing. This usage of Afaan Oromo language into today's internet technology in turn provide us with a huge sentiment data. Therefore, extracting this information and classifying it according to their degree of polarity by using machine-learning approach is the interest of this research.

Even though there is a rising usage of Afaan Oromo language for social media posts on the internet, there is no sufficient multi-scale sentiment assortment and cataloging method for the language. There are different multi scale sentiment analysis related researches conducted for English language (Gatti and Guerini, 2012; Rodrigues *et al*., 2015; Marchand *et al*., 2013) and Amharic (Wondwossen and Wondwossen, 2014) in this area, but sentiment analysis on Afaan Oromo language posts that are tried yet is only done using dictionary based approach (Eshetu, 2017; Jemal, 2018). The Amharic research, which was conducted by Wondowossen considers a small amount of corpus. Morphological property of Afaan Oromo language is not similar with Amharic and English language, so directly applying those research works on Afaan Oromo language is not appropriate. Even if Afaan Oromo language has complex structure, this thesis try to incorporate entire language features that infers sentiment. From the two Afaan Oromo sentiment analysis thesis discussed above, Jemal research only considered three common polarity rather than considering polarity strangeness and weakness and both of them used dictionary based approach which has small accuracy because it is limited to small sentiment words. With similar limitation, the study of sentiment mining for opinionated Amharic texts was examine using rule-based approach (Selama, 2010). The multi-scale property of the sentiment is very significant in order to rank the sentiment according to their strangeness, which in turn help to determine the opinion of the people on sensitive products or issues like politics. Doing the sentiment analysis by using positive, negative and neutral polarity level is humble because it only require identifying subjective features of the language. One of the challenging task in multi-scale sentiment analysis is identification of the polarity strength in different sentences of Afaan Oromo. For example, in the sentences "*Caaltuun baayyee baayyee bareedduu dha*" the word *bareedduu* (beautiful) is adjective and the word *baayyee* (very) is an adverb, so polarity is formed by following adverb with adjective. Such cluster of words, in this instance, make the sentiment to be more positive than having only the adjective *bareedduu* (beautiful).

In Afaan Oromo, polarity is expressed in advance of polarity strangeness such as Excellent (*Baayyee Baayyee Gaarii*), Very Good (*Baayyee Gaarii*), Good (*Gaarii/Misha*) .etc and weakness such as I never like it (ani *tasumaa kana hin jaalla dhu*), I do not like (*Ani hin Jaalla dhu*) etc. To fulfill this need, it is tempting to do multi-scale sentiment analysis. This study addresses the challenge of applying machine learning approach to the Afaan Oromo posts sentiment analysis and the possibility of doing multi-scale sentiment analysis. Thus, the target of this research is to develop a classifier for automatic multi-scale sentiment classification of Afaan Oromo posts into the five polarity levels. This may improve current activities of oral and survey based opinion mining and rule based sentiment classification that only consider the three polarity level positive, negative and neutral by adapting machine learning based multi scale sentiment analysis. Based on the discussion made above, in this research, the following research questions (RQ) are answered:

RQ 1: Which feature of Afaan Oromo language is appropriate to express the sentiment intensifiers?

RQ 2: What machine learning technique should be applied to perform multi scale sentiment analysis of Afaan Oromo social media posts?

1.3. Objective of the Study

General and specific objectives of the research given in the following two section 1.3.1 and 1.3.2 respectively.

1.3.1. General Objective

The general objective of this research is to investigate and develop a machine learning based multi scale sentiment analysis for the Afaan Oromo social media posts.

1.3.2. Specific Objective

In order to accomplish the general objective, the following specific objectives are formulated.

- ✓ Extensive review of available literatures on existing sentiment analysis methods for various language
- ✓ To study and analyze the structure of Afaan Oromo language with the intention of identifying and extracting features that aid to perform multi scale sentiment analysis of the Afaan Oromo language
- ✓ To identify the main source and approaches for collecting Afaan Oromo posts from internet and collect the required corpus
- ✓ To design and develop a model of machine learning based multi scale sentiment analysis that can be used to automatically classify Afaan Oromo posts in to their sentiment level
- ✓ To evaluate the Afaan Oromo multi scale sentiment analyzer model using accuracy, precision, recall and f-measure metrics.
- ✓ Forward future research work based on the investigation made

1.4. Scope and Limitation of the Study

This research attempted to extract multi-level sentiments from Afaan Oromo social media posts by applying supervised machine learning approach. Mainly it focus on comments, reviews and feedback posts which are usually brief and mirror opinions and individual feelings. Based on the experimental result of this study, applying machine learning for multi scale sentiment analysis of Afaan Oromo posts is acceptable. In this study, posts, which include Afaan Oromo as well as other language scripts in a single social media post (i.e multi lingual posts) and posts like photo, video sections, table sections, application sections, feeling sections, not covered. Instead, only the Afaan Oromo text reviews are considered for analyzing the sentiment. In addition to this, tasks such as sentiment spam detection, which identify whether the post is to give feedback or not, determining gesture based opinion and detecting misinforming comments not performed. Furthermore, feature or aspect level sentiment analysis and sentiment analysis for implied opinions, and or comparative opinions are out of scope of this research.

1.5. Significance of the Study

The research will provide the following benefits.

- ✓ Provide multi scale sentiment analysis for Afaan Oromo posts that give best feedback on services, products, peoples, political leaders, organization managers, governments etc. with their weakness and strength and which help to made decision depending on the sentiment they gain.
- ✓ Analyzing trends about consumer, competitors and market confusion of Oromia
- ✓ Monitoring critical issues to prevent negative viral effects on the areas someone engaged to serve Oromo people
- ✓ Tracking collective Oromo people user opinions and rating of products and services that are consumed by these people
- ✓ Creating Afaan Oromo opinion aggregation and review websites, recommendation systems
- ✓ Study insight of Oromo population regarding governmental policies; customers; new product development
- ✓ To be used for Afaan Oromo market research about brand awareness.
- ✓ To be used as input for Afaan Oromo morphological analyzer: text preprocessing, lemmatization, tokenization and part of speech tagging (POS), sentiment analyzer for different domain
- ✓ To provide subjective processing method of Afaan Oromo language.
- ✓ Provide Afaan Oromo sentiment corpus that can be used further for different sectors that need to process the sentiment of the Afaan Oromo language
- ✓ Used for researchers who need to do sentiment analysis on Afaan Oromo language for other domains.

2. LITERATURE REVIEW

In this chapter, numerous work carried out on sentiment analysis is reviewed to identify the gap and findings of the research and to have deep understanding about concepts and methods of sentiment analysis. Specially, some background literature on general sentiment analysis, types of sentiment analysis, components of sentiment analysis, levels of sentiment analysis, steps of sentiment analysis, classification approach of sentiment analysis, sentiment analysis evaluation methods, Afaan Oromo language and related works have been reviewed.

2.1. General Concepts of Sentiment Analysis

Sentiment is an extensive word, which may use to exemplify emotions, opinions, attitudes, views, outlooks, approaches, experiences etc. It may expressed in a form of text, speech, tweets, news, posts, database etc. The term subjective and emotion sentences are very close to sentiment. Subjective can be an objective sentence that describes some factual information about the world e.g., “iPhone is an Apple product” and subjective sentence which describes some personal feelings/emotions, views, or beliefs e.g., “I am glad with my MI phones”. The multi-scale or multi-polarity properties of sentiment is typically linked to the intensity of certain emotions such as love, joy, surprise, anger, sadness, fear etc. To handle both factual and emotional evaluations it is significant to apply multi-scale sentiment analysis to the opinions of the sentence. Sentiment analysis is a field in artificial intelligence (AI) which concern analysis of people’s opinions, sentiments, evaluations, outlook, approaches, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes towards some particular real world entity (Liu, 2012). Sentiment analysis also called opinion mining, subjectivity analysis or appraisal extraction. Presently, for distinguishing persons tempers regarding to some issue it is important to do analysis on the sentiment that are present on social media. Even sentiment analysis performed in the earlier, when people need to make significant decisions; they regularly asked their friends for their sentiments. In companies, to get valuable information customer surveys, blogs, opinion polls, focus groups and suggestion committees are used. Nowadays, with the extensive evolution of social media such as reviews, forum discussions, blogs, micro-blogs, twitters, comments, and posts in social network sites on the web, peoples use this social media to express their thoughts regarding some issue. Currently on domains like consumer products, individuals make services, healthcare, financial services, social events and politics important decisions and organizations are increasingly using the content in these social media. Because of this, it is pivotal to develop automatic system to collect and categorize opinions about a subject. As described in Tromp work, sentiment analysis is the process of automatically determining sentiment expressed in natural language (Tromp, 2012).

Sentiment analysis is a very rich research problem, with a large amount of work being published every year targeting the various aspects and dimensions of the problem (Saif, 2015). The complexities in conveyed texts cause an insufficiency to abide in the existing sentiment analysis studies, which identify user behaviors as well as their state of minds (Zamani *et al*., 2014). Clasification of human's opinions is challenging because of the polarity of the peoples sentiment. According to the author Salunkhe *et al*. (2017), basic sentiment analysis allows to determine or measuring the polarity of sentiment. In other words, it involves classifying opinions in text into categories like positive, negative, or neutral. Sentiment analysis is not simple task as it includes the study of NLP that process grammatical issues in order to identify the opinionated terms in the language.

2.2. Types of Sentiment or Opinion

According to Bing Liu sentiment is divided into two, regular opinion and comparative opinion (Liu, 2011).

2.2.1. Regular Sentiment

Often times this sentiment is denoted as opinion in the literature and it includes two main sub-types (Liu, 2011). These are direct opinion which denotes sentiment that expressed on an entity or an entity aspect, e.g.,"*Qulqullinni suura isaa baayyee bareedaa dha*" ("The image quality is very great"), and indirect opinion, this is the opinion which discussed indirectly on an entity or aspect of an entity reliant on its consequences on some other entities eg.,"*Erga Lammaa Magarsaa Bulchaa Oromiyaa tahanii muudamanii, jijjiiramni gaarii dhufuu eegale*" (" Good change is started in Oromia since Lammaa Magarsaa became Oromia regional state President") this defines desirable effect of Lammaa Magarsaa on Oromian policy which indirectly offers a positive sentiment to the Lammaa Magarsaa. Based on this example, the entity is Lammaa Magarsaa and the aspect is the effects on change. As it shown from above two examples, the complexity of sentiment analysis from direct opinion is very simple when compared with indirect opinion because in indirect opinion we can define the desirable and undesirable effect at a time on the same entity.

2.2.2. Comparative Sentiment

This states the similarity or difference relationship among two or more entities and /or a preference of the opinion holder based on some mutual aspects of the entities (Jindal and Liu, 2006). For example "*Appiliin Burtukaana caalaa mi'aawa, kanaaf Appiliin mi'aa bareedaa qaba*" ("Apple tastes better than Orange and Apple tests the best"). In addition to this classification, sentiment can be classified depending on how they are stated in text, explicit opinion and implicit (or implied) opinion (Liu, 2012).

2.2.3. Explicit Sentiment

This is a subjective statement that gives a regular or comparative opinion, e.g., "*Appiliin baayyee miyaawa," fi "Appiliin Burtukaana caalaa miyaawa*" ("Apple tastes great," and "Apple tastes better than Orange"). As it is shown in this example, explicit sentiment is clearly and unbiguously expressed or stated.

2.2.4. Implicit Sentiment

In contrary to explicit sentiment this is an objective statement that infers a regular or comparative sentiment. These often describes a desirable or undesirable facts, e.g., "*Baatiriin bilbila Tekinoo kan bilbila Xaanaa caalaa yeroo baayyeef tura*"("The battery life of Techno phones is longer than Tana phones"). An explicit sentiment is easy to identify and classify than implicit one. So, it is important to deal both explicit and implicit sentiment during sentiment analysis tasks.

2.3. Major Components of Sentiment Analysis

Sentiment analysis has three major components, sentiment holder, object and sentiment (Liu, 2007). Sentiment holders are one of a person, a group or an organization that holds a specific opinion on a particular object. Object is a product, person, an event, organization, topic or even an opinion. Sentiment holder is significant especially in news articles that contain different sentiment of different opinion holders e.g., people, organizations, and countries.

2.4. Sentiment Analysis Levels

Sentiment analysis can be performed at different levels of granularity with different levels of detail. According to Liu (2012), sentiment analysis can takes place in three levels: Document level sentiment analysis, Sentence level sentiment analysis and Entity or Aspect level sentiment analysis.

2.4.1. Document Level Sentiment Analysis

Document level sentiment analysis attempt to classify a whole a review document as either positive or negative (Pang *et al.*, 2002). In some cases, a neutral class is also considered.

2.4.2. Sentence Level Sentiment Analysis

Sentence level sentiment analysis finds sentiments from the sentences that demonstrates the sentence as positive, negative or neutral. It is closely related to subjectivity classification (Wiebe *et al.*, 1999), which differentiates objective sentences that states factual information of sentence and subjective sentences that states subjective views and opinions. In this level of classification, every single sentence is taken under consideration to analyses and express the opinion (Van Velthoven, 2014). Supported by this observation, the type of granularity that is preferable for social media posts is the sentence level sentiment analysis.

2.4.3. Entity or Aspect Level Sentiment Analysis

This level of sentiment analysis considers that an opinion contains both a sentiment (positive or negative) and a target (of the opinion). The goal of this level analysis is to find out sentiments/emotions on entities and/or aspect of those entities (Liu, 2012).

2.5. Basic Steps in Sentiment Analysis

According to Ali (2015), sentiment analysis has three main steps: sentiment retrieval, classification and summarization. Figure 2.1 has the architecture of sentiment analysis, which shows how the input is being classified on various steps to summarize the reviews.

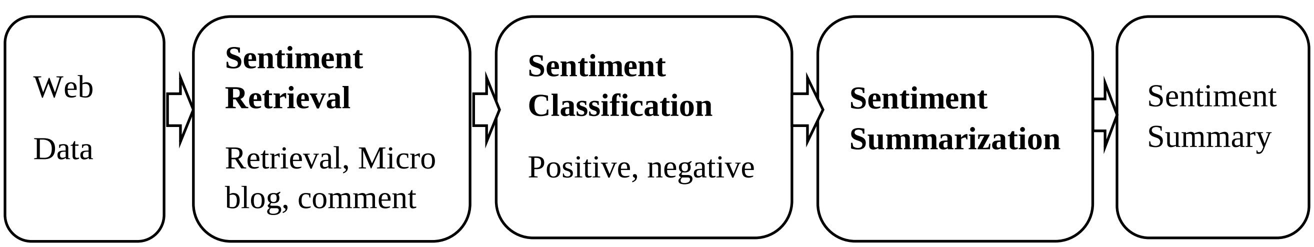

Figure 2. 1. Architecture of Sentiment Analysis (Ali, 2015)

2.5.1. Sentiment Retrieval

Sentiment retrieval is the process of gathering reviews, micro blogs, and comments of user from social media.

2.5.2. Sentiment Classification

Given an opinionated piece of text, the goal of sentiment classification is to classify the opinion as falling under one of sentiment polarities (negative, positive or neutral), or locate its position on the continuum between these polarities (Pang and Lee, 2008). Sentiment classification mainly consists of two important tasks, including sentiment polarity assignment and sentiment intensity assignment (Abbasi *et al.,* 2011). Sentiment polarity assignment deals with analyzing, whether a text has a positive, negative, or neutral semantic orientation. Most of the time this is done by detecting the subjectivity terms of the language. For example in the sentence, "*Laliseen baayyee bareeddi!*"("Lalise is very buetiful!"), the word beautiful is adjective which shows the positive sentiment. Sentiment intensity assignment deals with analyzing, whether the positive or negative sentiments are mild or strong. Consider the two sentences "*Si hin Jaalla dhu*" ("I don't like you") and "Baayyee *Sin Jibbaa*" ("I hate you very much"), both sentence are negative but the second sentence is more intense than the first. Sentiment intensity assignment task is more important for multi-level sentiment analysis as it considers the many intensifier of the language.

The sole challenges of sentiment classification task is to answer the question:" which feature of the language do we use?" in some researches the features such as term presence, opinion words and phrases (Liu, 2011), positions of words, part-of-speech, syntax and negation are used to limit the classification challenge (Pang *et al.*, 2002; Mejova, 2009). The explanation of the term presence, opinion words and phrases, n-grams, part-of-speech, syntax and negation are given in the following.

- **Term Presence**

Term presence improve the sentiment classification task (Pang and Lee, 2008). In the term based features, document representation emphasizing term presence contain 1 if term appears in the document at least once, 0 otherwise.

- **Opinion Words and Phrases**

These words are regularly used to express positive or negative sentiments. For example, beautiful, wonderful, good, and amazing are positive opinion words, and bad, poor, and terrible are negative opinion words. Although many opinion words are adjectives and adverbs, nouns (e.g., rubbish, junk, and crap) and verbs (e.g., hate and like) can also indicate opinions. Not only single terms, there are also sentiment phrases and idioms, e.g., cost someone an arm and a leg. Opinion words and phrases are instrumental to sentiment analysis for obvious reasons.

- **Word positions**

Term positions are also significant in representing the document for sentiment analysis. The position of terms decides, and sometimes reverses/flips, the polarity of the sentence. So, position information is sometimes encoded into the feature vector (Pang and Lee, 2008).

- **Part-of-Speech**

Adjectives are good pointers of sentiment in text. For example, Turney (Pang *et al.*, 2002) uses part-of-speech patterns, most containing an adjective or an adverb, for sentiment detection.

- **Syntax**

Syntax information may contain vital text features such as negation, intensifiers, and diminishers, which use for sentiment analysis (Kennedy and Inkpen, 2006).

- **Negations**

Negations reverses the polarity of the sentence by coming before the word, for example in these two Afaan Oromo sentences "*Sin Jaalla dha*"("I love you") and"*Si hin jaalla dhu*"("I don't like you"), the word *Jaalla* is negated by *hin*(not) negation.

2.5.3. Sentiment Summarization

In this stage, sentiment summary of reviews delivered should be recognized on features or subtopics that are stated in the reviews. The sentiment summarization process mainly done using the following two approaches (Talati *et al.*, 2014), feature based summarization and term frequency based summarization.

i. Feature Based Summarization

This involves finding of frequent terms (features) that are appearing in many reviews. Features present in review text can be identified using Latent Semantic Analysis (LSA) method (Balahur *et al.*, 2012). LSA method forms a term-document co-occurrence matrix. In this matrix terms represents rows and column represent documents. This matrix shows term frequency of every term in a document. By applying singular value decomposition (SVD) method to the above matrix as (Jayasekara, 2016).

$$A = USV^T \qquad \text{Equation 1}$$

Where U & V are matrices with orthonormal columns (i.e. UU^T=VV^T = 1) and S is a diagonal matrix of A. Rows of resultant matrix represents most important terms (features). Sentences that contain these terms can be presented in a summary.

ii. Term Frequency Based Summarization

Term frequency summarization method count occurrence of the term in a document. In many product reviews certain product features appear frequently and associated with user opinions about it. In this method, sentences are scored by term frequency (Tsytsarau and Palpanas, 2012). After calculating term frequency of each term, summary is obtained by choosing sentences that contain highest frequency terms.

2.6. Fine-grained Sentiment Analysis

Sometimes it is crucial that considering more precise about the level of polarity of the opinion, so instead of just talking about positive, neutral, or negative opinions the multi-polarity levels like very positive, positive, neutral, negative and very negative are looked at, this is generally referred to as fine-grained sentiment analysis. This could be, for example, represented by 5-star rating in a review, e.g.: very positive = 5 stars and very negative = 1 star. Some systems also give different flavors of polarity by recognizing if the positive or negative sentiment is linked with a specific feeling, such as, anger, sadness, or worries (i.e. negative feelings) or happiness, love, or enthusiasm (i.e. positive feelings).

2.7. Common Classification Approaches to Sentiment Analysis

As it illustrated in Pang et al., two methods of sentiment classification are there; machine learning method and lexicon method (Pang *et al.,* 2002). Figure 2.2 shows the big picture of sentiment classification techniques.

2.7.1. Machine Learning Approaches

Machine learning provides systems the capacity to automatically learn and advance from knowledge without being explicitly programmed. The sentiment analysis task is usually modeled as a classification problem where a classifier is fed with a text and returns the corresponding category, e.g. positive, negative, or neutral (in case polarity analysis is being performed). The model of sentiment analysis is developed with labeling text into their sentiment. It involves two steps: 1) it requires some collection of labelled sentiment corpus to train a model 2) prediction of new or unlabeled set of data based on training model. In general, classification tasks in machine learning are often divided into several sub-tasks:

- ✓ **Data preprocessing:** This remove the incomplete, noisy and inconsistent data. It includes tasks such as filtering, removing stop words, tokenization, stemming, removing punctuations, removing numbers and white space, normalization etc.
- ✓ **Feature selection and/or feature reduction:** These attempts to reduce the dimensionality (i.e. the number of features) for the remaining steps of the task. Further reduction of vector size can lead to more improvements if the features are noisy or redundant.
- ✓ **Representation:** After key features are considered, the text data is represented by vectors, which are used for the classification task.
- ✓ **Classification:** This phase finds the actual mapping between patterns and labels (or targets) based on the polarity and intensity of the text using any of the machine learning approaches.

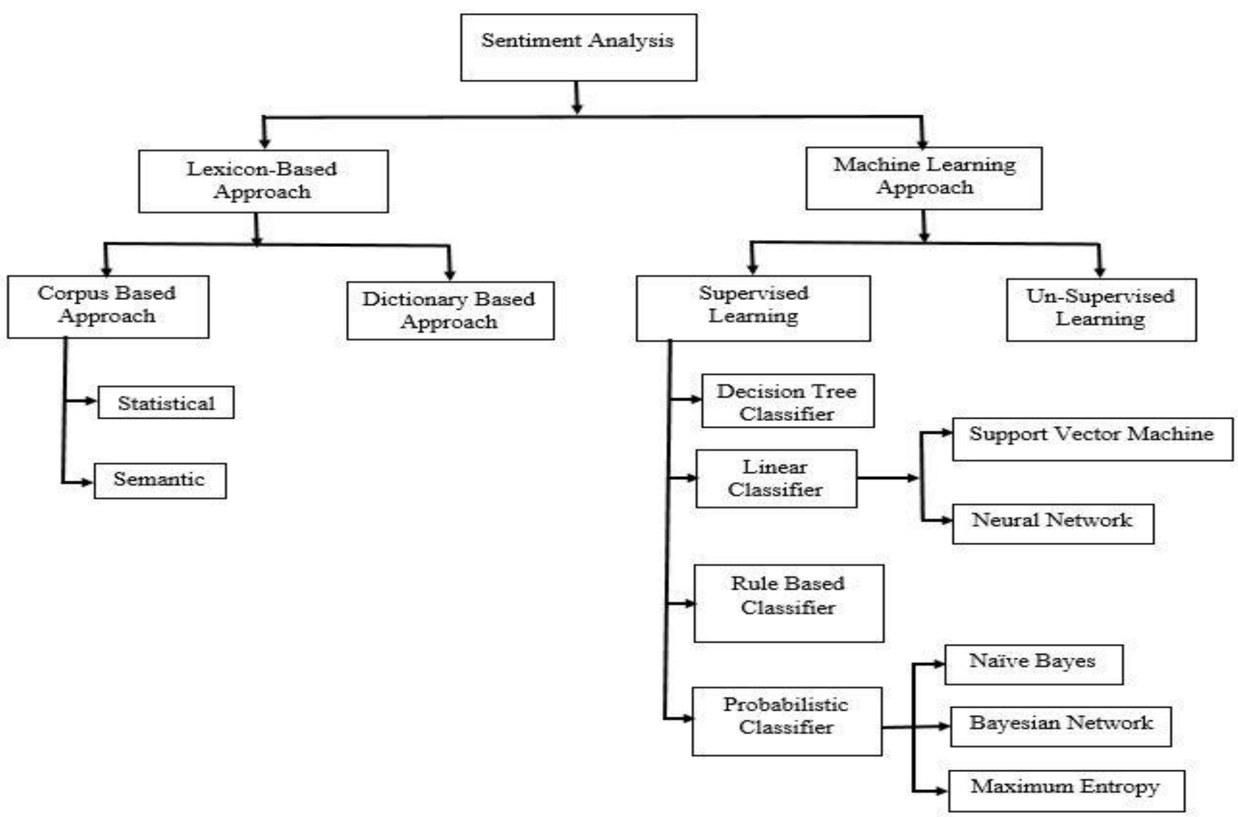

Figure 2. 2. Sentiment analysis approaches (Medhat, 2014)

Machine learning technique is further divided into two main approaches i.e. supervised learning approach and unsupervised approach (Pang *et al.*, 2002).

2.7.1.1. Supervised learning approach

In this approach, the classification model made during the learning phase, on representative sets of training documents focused on the topics of interest. In sentiment classification sentiment terms that specify polarity of opinions are essential, e.g., great, excellent, amazing, horrible, bad, worst, etc. (Liu, 2011). Supervised classifier can usually be implemented with the following steps and components:

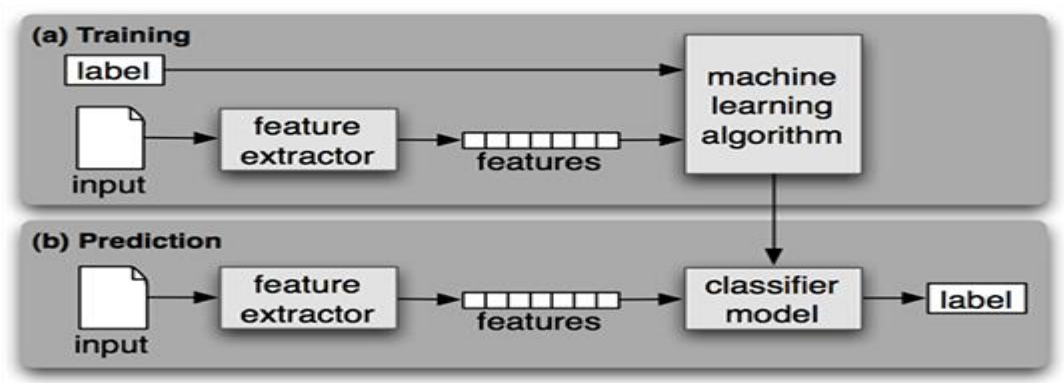

Figure 2. 3. Frameworks for Supervised Classification (Bird et al., 2009)

In the training process (a), the model learns to associate a particular input (i.e. a text) to the corresponding output (tag) based on the test samples used for training. The feature extractor transfers the text input into a feature vector. Pairs of feature vectors and tags (e.g. *positive*, *negative*, or *neutral*) are fed into the machine learning algorithm to generate a model. In the prediction process (b), the feature extractor is used to transform unseen text inputs into feature vectors. These feature vectors are then fed into the model, which generates predicted tags (again, *positive*, *negative*, or *neutral*).

Machine learning field provides many algorithms for classifying text to its sentiments. Given the training data, existing supervised learning methods can be readily applied to sentiment classification, e.g., Support Vector Machine (SVM), MaximumEntropy(MaxEnt), Naïve Bayes(NB) etc. (Pang *et al.*, 2002).

A. Naïve Bayes Classification

Naive Bayes is an approach to text classification that assigns the class $c^* = \text{argmax}_c\ P(c \mid d)$, to a given document *d*. It is based on Bayes' probability theorem and predominantly used when the dimensionality of the inputs are high. A few examples are spam filtration, sentimental analysis, and classifying news articles. Its underlying probability model can be defined as an "independent feature model". The NB classifier uses the Bayes' rule Eq. (2),

$$P(c \mid d) = \frac{P(c)P(d \mid c)}{P(d)}$$ Equation 2

Where, *P (d)* plays no role in selecting c^*. To estimate the term *P(d | c),* NB decomposes it by assuming the f_i's are conditionally independent given d's class as in Eq.(3),

$$P_{NB}(c \mid d) = \frac{P(c)\left(\prod_{i=1}^{m} P(f_i \mid c)^{n_i(d)}\right)}{P(d)}$$ Equation 3

Where, m is the no of features and f_i is the feature vector. Consider a training method consisting of a relative-frequency estimation *P(c)* and *P* $(f_i \mid c)$.

Despite its simplicity and the fact that its conditional independence assumption clearly does not hold in real-world situations, Naive Bayes-based text categorization still tends to perform surprisingly well (Lewis, 1998); indeed, Domingos and Pazzani (1997) show that NB is optimal for certain problem classes with highly dependent features. Many researchers used NB algorithm for classification of social media posts into their polarity and emotion.

B. Maximum entropy Classification

Maximum Entropy classification is yet another technique, which has proven effective in a number of NLP applications. (Berger et al., 1996) show that it sometimes, it outperforms NB at standard text classification. Its estimate Of *P(c | d)* takes the exponential form as in Eq. (4) [10],

$$P_{ME}(c \mid d) = \frac{1}{Z(d)} \exp\left(\sum_i \lambda_{i,c} F_{i,c}(d,c)\right)$$ Equation 4

Where, *Z (d)* is a normalization function. *Fi, c* is a feature/class function for feature fi and class *c*, as in Eq. (5),

$$F_{i,c}(d,c') = \begin{cases} 1 & n_i(d) > 0 \text{ and } c' = c \\ 0 & \text{otherwise} \end{cases}$$ Equation 5

For instance, a particular feature/class function might fire if and only if the bigram "still hate" appears and the document's sentiment is hypothesized to be negative. Importantly, unlike NB, MaxEnt makes no assumptions about the relationships between features and so might potentially perform better when conditional independence assumptions are not met. The λ_i,c*'s* are feature-weight parameters; inspection of the definition of *P*ME shows that a large λ_i,c means that f_i is considered a strong indicator for class *c*.

C. Support Vector Machine Classification

Support vector machine is a "supervised classification technique which is based on maximum margin linear discriminants" (Banitaan, 2010). The SVM uses a "kernel function approach to map an input feature space into a new space where the classes are linearly separable" (Banitaan, 2010). Support vector machine have been shown to be highly effective at text categorization, generally outperforming Naive Bayes (Joachims, 1998). They are large-margin, rather than probabilistic, classifiers, in contrast to NB and MaxEnt. In the two-category case, the basic idea behind the training procedure is to find a maximum margin hyperplane, represented by vector $\vec{w}$, that not only separates the document vectors in one class from those in the other, but for which the separation, or *margin*, is as large as possible. This corresponds to a constrained optimization problem; letting $c_j \in \{1, -1\}$ (corresponding to positive and negative) be the correct class of document *dj*, the solution can be written as in Eq.(6), w

$$\vec{w} := \sum_j \alpha_j c_j \vec{d}_j, \quad \alpha_j \geq 0 \qquad \text{Equation 6}$$

where, the *αj*'s (Lagrangian multipliers) are obtained by solving a dual optimization problem. Those $\vec{d_j}$ such that *αj* is greater than zero are called *support vectors*, since they are the only document vectors contributing to $\vec{w}$. Classification of test instances consists simply of determining which side of $\vec{w}$'s hyperplane they fall on.

In the work of classifying movie into two classes, positive and negative (Pang *et al.,* 2002) shows that using unigrams (a bag of individual words) as features in classification performed well with either NB or SVM. The studies also show that SVM is effective, accurate, and can work well with small amount of training data (Lin and Ngo, 2007).

2.7.1.2. Unsupervised learning approach

The main purpose of unsupervised learning is to model the principal structure or distribution in the data in order to learn more about the data. Unlike supervised learning, there is no exact solutions and there is no trainer. Algorithms are used in determine and present the interesting structure in the data. In sentiment analysis task, unsupervised learning methods focus on opinion words and phrases.

2.7.2. Lexicon Approaches

In lexicon-based technique, classification is done by matching the features of a given text along sentiment lexicons whose sentiment values are determined prior to their use.This includes three main approaches: manual approach, dictionary-based approach, and corpus-based approach (Vohra, 2013). The manual approach opinions are classified depending on the linguistic knowledge and the sentiment summary is calculated manually. In dictionary-based approach, the dictionary of different sentiment words and phrases with their associated orientations, intensification and strength are stored and sentiment score for each words and phrases is computed depending on this sentiment word dictionary (Taboada et al., 2011). In other hand, corpus based techniques rely on syntactic or co-occurrence patterns and also a seed list of opinion words to find other opinion words in large corpora (Liu, 2010).

2.8. Sentiment Analysis Metrics and Evaluation Methods

Effectiveness of sentiment classification systems are evaluated using the same measures as standard text classification algorithms via precision, recall, f-measure or f1-Score, and accuracy (Padmaja and Fatima, 2013). The calculation of this metrics is done based on confusion matrix (Table 2.1). Confusion matrix contains the estimated and actual distribution of labels. Each column corresponds to the actual label and each row corresponds to the estimated label of the sentence.

	True Sentiment Positive	**True Sentiment Negative**
Classified Positive	TP	FP
Classified Negative	FN	TN

Table 2.1. Confusion matrix of a classifier

Where

TP: the number of correct classifications of the positive examples (**true positive**)

FN: the number of incorrect classifications of positive examples (**false negative**)

FP: the number of incorrect classifications of negative examples (**false positive**)

TN: the number of correct classifications of negative examples (**true negative**)

Accuracy measures how many texts were predicted correctly (both as belonging to a category and not belonging to the category) *out of all of the texts* in the corpus. The accuracy is determined using the equation:

$$Accuracy = \frac{TP+TN}{Total} \quad \text{Equation 7}$$

Most frequently, precision and recall are used to measure effectiveness because does not shows how good or bad the classifier algorithm is. Precision measures how many texts were predicted correctly as belonging to a given category out of all of the texts t*hat were predicted (correctly and incorrectly) as belonging to the category.* It calculated as:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FN}} \qquad \text{Equation 8}$$

The greater precision the less number of false hits. However, precision does not show whether all the correct answers are returned by the classifier. In order to take into account the latter recall is used. Recall measures how many texts were predicted correctly as belonging to a given category out of all the texts that *should have been predicted as belonging to the category*. Defined by the equation:

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FP}} \qquad \text{Equation 9}$$

The more precision and recall the better. However, simultaneous achievement of the high precision and recall is almost impossible in real life that is why the balance between two metrics has to be found. F-Measure/F1-score is a harmonic mean of precision and recall:

$$\text{F} - \text{Measure} = \frac{\text{2xPrecisionxRecall}}{\text{Precision+Recall}} \quad \text{Equation 10}$$

2.9. Afaan Oromo Language

2.9.1. Introduction of Afaan Oromo Language

Afaan Oromo is one of the major African languages that is widely spoken and used in most parts of Ethiopia and some parts of other neighbor countries like Kenya and Somalia (Debela, 2011). Currently, Afaan Oromo is an official language of Oromia regional state. Oromia regional state is the largest regional state among the current federal states in Ethiopia, which amounts to 34.5% of the total population according to the 2008 census.

In Oromia regional state, it used in courts, in schools and for administration etc. As well, Afaan Oromo is the instructional medium for primary schools and given as an independent subject in secondary schools throughout the region. Furthermore, a few literature works, a number of newspapers, magazines, educational resources, official credentials and religious documents are published and available in the language.

2.9.2. Afaan Oromo Writing System

All letters in English language are also in Afaan Oromo except the way it written. The writing system of Afaan Oromo language is straightforward which designed based on the Latin script called *Qubee* Afaan Oromo. In 1991, Qubee was established as the official alphabet of the Afaan Oromo language (Tilahun, 2006). Totally, Afaan Oromo has thirty-three sounds/characters. These thirty-three letters referred to as *Qubee*, the Oromo alphabet. *Qubee* is the symbol that used to represent sound to form a meaningful word. *Qubee* includes vowel letters (‘a/A’, ‘e/E’, ‘i/I’, ‘o/O’,‘u/U’), consonant letters (b, c, d, f, g, h, j, k, l, m, n, q, r, s, t, w, x, y, z), doubled consonant letters or digraphs (‘ch/CH’, ‘dh/DH’, ‘sh/SH’,‘ph/PH’, ny/NY), and the letters borrowed for foreign words(p/P, v/V, ts/TS and zy/ZY) (Bekama, 2007). In Afaan Oromo language alphabets are written in two forms, in capital letters and small letters. Afaan Oromo capital letters : A, B, C, CH, D, DH, E, F, G, H, I, J, K, L, M, N, NY, O, P, PH, Q, R, S, SH, T, TS, U, V, W, X, Y, Z, and ZY ; Afaan Oromo small letters: a, b, c, ch, d, dh, e, f, g, h, i, j, k, l, m, n, ny, o, p, ph, q, r, s, sh, t, ts, u, v, w, x, y, z, and zy.

Afaan Oromo has the typical Eastern Cushitic set of five short vowels: a/A, e/E, i/I, o/O, u/U and five long vowels by doubling the five vowel letters: “aa/AA”, “ee/EE”, “ii/II”, “oo/OO”, “uu/UU” with their small and capital letters. Consonants, on the other hand , do not differ greatly from English, but there are few special combinations such as “ch” and “sh” (same sound as English), “dh” in Afaan Oromo is like an English “d” produced with the tongue curled back slightly and with the air drawn in so that a glottal stop is heard before the following vowel begins. Another Afaan Oromo consonant is “ph” which made when with a smack of the lips toward the outside. “ny” closely resembles the English sound of “gn”.

In contrasting to English or other Latin based languages there are no skipped or unpronounced sounds/alphabets in the language. Every alphabet is to be pronounced in a clear short/quick or long /stretched sounds. In a word where consonant is doubled the sounds are more emphasized/stretched. Moreover, in a word where the vowels are doubled the sounds are elongated and if a single vowel with single consonant is used it shorten the sound. Elongating and shortening vowels, doubling and shortening consonants give a word different meaning. Afaan Oromo single consonants does not give us a sound, whereas they put before or with vowels to form a sound.

2.9.3. Afaan Oromo Morphology

Morphology is a branch of linguistic that studies morphemes and their arrangements in forming words (Assefa, 2005). Morphemes are the smallest and building blocks of linguistic unit, which may create words or parts of words. Morphemes has two classes, these are stems and affixes (prefix, infix and suffix). The stem is the core morpheme of the word, providing the core meaning while affixes are used to add extra meaning to words (Abebe, 2010).

Like in a number of other African and Ethiopian languages, Afaan Oromo has a very complex and rich morphology (Debela, 2011). It is one of the language that has agglutinative characteristics comprising very wide inflectional and derivational morphological processes (Debela, 2011). Agglutination is the process in linguistic morphology derivation in which complex words are formed by stringing together morphemes without changing them in spelling or phonetics, and languages that use agglutination widely are called agglutinative languages (Gadisa, 2013). In the languages which has Agglutination property similar to Afaan Oromo, grammatical formation are usually carried out through affixes (infix, prefixes and suffixes) attached to the root or stem of words. Afaan Oromo words have some prefixes and infixes whereas suffixes are the predominant morphological features in the language (Tesfaye, 2010).

In Afaan Oromo, words are formed by either inflectional morphology or derivational morphology (Debela, 2010). Afaan Oromo inflectional morphemes does not change the meaning of the stem and or word they collocated. In Afaan Oromo word categories such as nouns, adjectives and verbs, inflectional morphemes modify a word's numbers (plural), tenses, aspect, persons, possessions etc. Some of inflectional affixes in Afaan Oromo are*: -ota, -een, -yyii, -oota, -dhaan, -lee, -wwan, -dhaaf, -fi, -tuu, -te, -e, -an, -f, –n, -een, -ichaa, -tu, -oo, -oota, -eessa/-eettii, -a/-ttii or –aa/tuu.* etc. Example, collocating a suffix *–tuu* to a noun *barsiisaa* (teacher):masculine will create an inflected noun *barsiistuu (teacher):feminine.*

In other hand, Afaan Oromo derivational affixes change the meaning and the category of the word class, and derive new words through collocation to root morphemes. In Afaan Oromo, they may be suffixes or prefixes. Some of the derivational affixes in Afaan Oromo are: *hin-, -eenya, -ummaa, '–achuu','-lee','-eenyaa','-ina'* and etc. Example, collocating *–ina* suffix to an adjective "*gowwaa"(fool)* will derive a new noun called "*gowwummaa"(foolishness)*.

The semantic processing tasks in Afaan Oromo (e.g., Afaan Oromo sentiment analysis) ran into various challenges due to the extensive inflectional and derivational features of the language. Morphological analysis tasks such as tokenization, stemming, lemmatization etc. plays significant role in the semantic processing tasks.

2.9.4. Afaan Oromo Word Categories

Word is a single unit that made from combination of sounds or letters by following grammatical rules (Geetaachoo, 2007). The combination of two or more meaningful words depending on the structure of the language provide us phrase, clause or sentence. The meaning of the sentence can be determined by different arrangement of the words and depending on the meaning of each words that found in the sentence. For the languages that follow Latin Scripting the word in the sentence is delimited by the space. In Afaan Oromo, words in the sentence are categorized into eight (8) different classes according to their function in it (Bekama, 2007). These are called part of speech of Afaan Oromo. These are *maqaa* (noun), *bamaqaa/maqdhaala* (pronoun), *ibsa maqaa*/Addeessa (adjective), *xumura/gocha* (verb), *ibsa xumura/dabalgocha* (adverb), *maqduubee*(postposition ="preposition in English") ,*qarqabduu /qabsiisee* (conjunctions), *dinqifannoo/dinqifata* (Interjection).

I. Noun (*Maqaa*)

A term that is used for giving a name to a person, place, thing, quality, idea or an action is called a noun (Wassinee, 2017). Afaan Oromo nouns ends with different sounds such as *–ina, -eenya, -ummaa, -maya, -maata, -iinsa* etc. Nouns can be classified under five different names (Getaachoo, 2007). These are proper nouns: e.g., *Caalaa* (name of person), *Finfinnee* (name of town), *Oromiyaa* (name of country) etc. collective nouns: e.g., *Mootummaa* (Government), *Polisii* (Police), *Ummata* (People), *Saba* (Community) etc. common nouns: e.g., *Biyya* (Country), *Nama* (Human), *Barataa* (Student), *Haroo* (Lake) etc. material nouns: e.g.,*Waraqaa* (paper),*Siree* (bed), *Barcuma* (Chair) etc. and abstract nouns: this is used to express quality of something. E.g. *bilissummaa* (Freedom), *hiyyummaa* (Poorness), *gabrummaa* (Slavery) etc. Afaan Oromo nouns can be formed by attaching different derivational suffixes to different word categories such as adjective, noun, verb etc. For instance, nouns are made from adjectives by adding *–ina, -ummaa,* and *-eenya* suffixes. A nouns are formed from verbs by adding *–maata, -maatoota, -maya, -mayoota, -a, -aa, -ii, -oo, -uu, -nnoo , -tuu, -duu, -xuu, -ituu, -iinsa(-uumsa)* nominalizers to the stem of the verb. Furthermore, nouns can be made from other noun by deriving it using *–ooma, -oomii* suffix. In order to understand noun formation consider the following three examples.

Adjective	**Noun**
Fokkisaa (ugly)	*Fokkina*(ugliness)
Gowwaa (fool)	*Gowwummaa* (foolishness)
Jabaa (strong)	*Jabeenya* (strongness)

Noun formation from adjectives examples

Noun	**Derived Noun**
Nama (human)	*Namooma*(Humanity)
Nama (human)	*Namoomii*(Humanity)

Noun formation from another noun Examples

Verb Stem	**+**	**Nominalizer**	**=**	**Derived Noun**
Fur	+	*maata*	=	*furmaata (Solution)*
Jaar	+	*maya*	=	*jaarmaya* (media)
Yaada	+	*a*	=	*yaada* (idea)
Dhoww	+	*aa*	=	*dhowwaa (forbidden)*
Haww	+	*ii*	=	*hawwii* (name of person)
Rakk	+	*oo*	=	*rakkoo* (problem)
Kuf	+	*iinsa*	=	*kufiinsa* (fail)
Bit	+	*tuu*	=	*bittuu* (buyer)
Qaroom	+	*mii*	=	*qaroomii* (civilization)

Noun formation from verb stem and nominalizer examples

II. Pronoun (*Maqdhaala*)

Pronoun is a word that used instead of a noun or noun phrase (Bekama, 2007). Oromo pronouns have the following features:

- person: 1st, 2nd, 3rd
- number: singular and plural
- case: nominative, genitive, dative, accusative, instrumental, ablative, locative
- 2nd person plural can also be used as a polite form of address
- There is a gender distinction in the 3rd person singular but not in the plural.

- There is a distinction between proximal and distal demonstrative pronouns, e.g., *kana* ‘this’ and *san* ‘that.’

A number of pronouns are there in Afaan Oromo, namely: personal pronouns, demonstrative pronouns, relative pronouns, and interrogative pronouns, reflexive and reciprocal pronouns, possessive pronouns (Getaachoo, 2007).

- ❖ **Personal Pronouns**

In Afaan Oromo personal pronouns stands for three persons: 1st person, 2nd person and 3rd person. Like English, Afaan Oromo uses different forms of personal pronouns to indicate their role in the sentence. While “he” and “him” may refer to the same person, English uses “he” for subjects and “him” for objects. Personal pronouns can be used to replace the subject and the object of a sentence (Abebe, 2015). Personal pronouns used to represent subject of the sentence are *Ani* (I), *Ati* (you), *Inni* (he), *ishiin* (she), *Nuyi/nuti* (we), *isiin* (you) and *isaan* (they). Personal pronouns that can replace objects of the sentence are *Ana* (me), *si* (you), *isa* (him), *ishii* (her), nu (us), *isiin* (you) and isaan (they).

- ❖ **Demonstrative Pronouns**

Demonstrative Pronouns used to refer to objects mentioned earlier or which are already present in the speakers mind. Some of Afaan Oromo demonstrative pronouns are *kun* (This) as subject, *kana* (This) as object, *sun* (That) as subject, *sana* (That) as object, *sunniin/sanneen* (Those), *kunniin/kanneen* (These), *kan akkanaa* (Such), *waa* (one).

- ❖ **A relative pronouns**

A relative pronoun is a joining pronoun. The relative pronouns of Afaan Oromo are *isa, inni, ishee, warri, warra, isheen* etc. The English meaning of this relative pronouns depend on the context of the sentence.

- ❖ **Interrogative pronouns**

Interrogative pronouns are used in questions, and come before the verb and either before or after the subject. Often, if the verb is “is/are”, this verb is dropped when using an interrogative pronoun. The main interrogative pronouns in Afaan Oromo are: *maal* (what), *kam* (which), *eenyu* (who), *eessa* (where), *akkaamitti/attam/akkaam* (how), *maaliif* (why), *kan eenyu* (whose) *meeqa* (how much, many).

❖ **Reflexive pronouns**

Oromo has two ways of expressing reflexive pronouns ('myself', 'yourself', etc.). One is to use the noun meaning 'self': of (i) or if (i).This noun is inflected for case, but unless it is being emphasized, not for person, number, or gender. E.g. *isheen of laalti* 'she looks at herself' (base form of *of*), *isheen ofiif makiinaa bitte* 'she bought herself a car' (dative of *of*).The other possibility is to use the noun meaning 'head', *mataa*, with possessive suffixes: *mataa koo* 'myself', *mataa kee* 'yourself (s.)', etc.

❖ **Reciprocal pronoun**

Oromo has a reciprocal pronoun wal (English 'each other') that is used like of/if. That is, it is inflected for case but not person, number, or gender. E.g. *wal jaalatu* 'they like each other' (base form of wal), *kennaa walii bitan* 'they bought each other gifts' (dative of *wal*).

❖ **Possessive pronouns**

Possessive pronouns are used to indicate the ownership of something. In Afaan Oromo possessive pronouns are indicated by suffixes and expressed by singular and plural form. Singular: *Kiyya* (my/mine), *Kansaa* (his), *Kanshii* (hers), *Kessaanii* (yours). Plural: *Keenyaa* (ours), *Kan isaanii*(theirs).

III. Adjective (*Addeessa*)

An adjective is a word that is used to add something to the meaning of the noun to show the quality of things (Wassinee, 2017). In Afaan Oromo the adjectives come after the noun or the pronoun they qualify. Nevertheless, in English they are placed before. Consider the following examples

- ✓ *Oromiyaan Biyya Bareedduu dha* (Oromia is beautiful country)
- ✓ *Nama gaarii* (A good man)

In above two examples the word *bareedduu* and *gaarii* are adjectives.

Afaan Oromo adjectives are highly inflected for gender, person, number, tenses. Afaan Oromo adjectives are formed by attaching one of adjective affixes, noun affixes or verb affixes on the root or stem of the word. Some of these suffixs are –a, -aa, -oo,-uu,-saa, -e, -eessaa, -oota, -ooli, -wwan, -lee, -an, -een, -icha, -ittii, -cha,-ota,-ni,-n, -i,-ti,-ttii,-tuu,-eettii,-tuu,-t etc. In addition to this, there is a case in which noun and verb is used as the adjective in the context of the sentence. For example: *ni bareeddu* (you are beautiful). In this example, the word *bareeddu* is verb but it is used as adjective contextually. There are many words that are adjective by their nature. Some of these words are *bareedaa* (handsome), *bareedduu* (beatiful), *sooressa* (rich), *hiyyeessa* (poor), *jabaa* (strong), *gaarii* (good), *gadhee* (bad), *laafaa* (loose), *gubaa* (hot), *abshaala* (clever), *bunee* (brown), *rakkisaa* (difficult), *gowwaa* (fool) etc. Adjectives are divided into eight groups (Getaachoo, 2007).The adjective types along with their description are given in the following.

- **Descriptive Adjectives:** Describe the quality of a person or thing. Example: *Intala Bareedduu* (A beautiful girl).
- **Adjectives of Quantity:** Illustrates the amount of the noun they describe and extremely useful when describing things. Some words of Afaan Oromo adjective of quantity indicators are: *Waa* (some), muraasa/xinnoo (alittle), *baayyee* (many), *hundumtuu* (all), *hedduu* (more), *hunda* (several), *baayyee xinnoo* (little). Example: *Haramaayaatti barattoota hedduutu barata* (Many students study in Haramaya).
- **Adjective of Degree:** incrementally increase or decrease adjective intensity. In Afaan Oromo the same words that used in adjective of quantity also used for adjective of degree. Example: *Tolaan Baay'ee cimaadha* (Tola is very intelligent)
- **Adjective of Numbers or Orders:** These may be use ordinal or cardinal numbers to express nouns in the sentence. For examples: *Burtukaana laman nyaadhe* (I have ate two Oranges), *Caalaan kutaa 8^{ffaa} keessatti tokkoffaa bahe* (Caalaa stood first in grade eighth).
- **Possessive Adjectives:** Used to express possession of something: *koo* (my), *kee* (your), *isaa* (his), *ishee* (her), *keenya* (our), *keessan* (your), *isaanii* (their). Example: *Kun mana kooti* (This is my house).
- **Demonstrative Adjectives:** demonstrate a quality about the noun they modify: *Kana/Kun* (this), *Sana*/*Sun* (that), *kanneen* (these), *Sanneen* (those) and *akkanaa* (such). Example: *Gurbaan sun baayyee miidhagaadha* (That boy is very handsome).
- **Distributive Adjectives:** used to refer to each object in a group of things: *tokko* (each), *tokko* (every), *abbi-tokko* (either one), *tokko'yyuu* (neither one), *tokko tokko* (each one). Example: Abbi-tokko kottaa (come either of you)
- **Interrogative Adjectives:** modify nouns and are used in interrogative sentences (i.e., questions): *Maal* (what), *kam*/*kami* (which), *eenyuu* (whose), *hammam* (how much), *meeqa*

(how many), *attam* (how) etc. Example: *Mallaqa meeqa qabda? (H*ow many money do you have?)

IV. Verb (*Gocha*)

A verb tells what some body or something does, in what state somebody or something is, or what is happening to somebody or something .etc. (Bekama, 2007). In Afaan Oromo, verbs mostly appear at the end of sentence. Example: *'Firaa`ol Adaama deeme'* (Fraol went Adaama). In this example, the word *deeme* (went) is the verb and it is found in the end of the sentence.

In Afaan Oromo, the infinitive of most verbs ends in –u. Afaan Oromo verbs can be categorized into main (transitive or intransitive) and auxiliary verbs (Diriba, 2002). Intransitive verbs are main verbs which do not take object or complement in a sentence (Getachew, 2009). Transitive verbs are main verbs, which transfer message to complement (objects). Auxiliary verbs support the main verbs used in a sentence. The following are Afaan Oromo auxiliary verbs *'dha'*, *'ta,e', 'qabda', ture, 'jira',* etc(Abebe, 2015). For examples:

- ✓ *'Isheen barattu cimtu dha.'* (She is a clever student.)
- ✓ *'Hojii kana hojjechuu qabda.'* (You have to work this job.)

In the above examples, the word *'dha'* and *'qabda*' are auxiliary verbs.

V. Adverb (*Dabalgocha*)

Adverbs are words that are used to add something or modify the meaning of a verb, an adjective, and another adverb and a preposition (Wassinee, 2017). In Afaan Oromo adverbs come before the verb or adjective they modify. Example: *Namichi baayyee bareedaa dha* (the man is very handsome). In this example, the word *bareedaa* is adjective, *dha* is verb, and *baayyee* is adverb. Afaan Oromo adverbs are categorized as adverbs of time, place and manner and adverb of reason (Getachoo, 2007).

❖ **Adverbs of time**

Adverbs of time show the time the action takes place. The following are the words that can be used as adverbs of time in Afaan Oromo language. *Har'a* (today), *kalleessa* (yesterday), *iftaan* (the day after tomorrow), *wagga dhufu* (next year), *bardheengaddaa* (last year), *torban borii* (on the week of tomorrow), *gaafa wixataa* (on monday), *ganamaan* (by morning), *ji'adhufu* (next month), *amma* (now), *boru*(tomorrow), *kaleessa* (yesterday), *yoom* (when), *har'a* (today), *galgala* (tonight) etc. Example: *Marartuun kaleessa deemte* (Marartuu went yesterday). In this example, the word '*kaleessa'* (yesterday) shows adverbs of time.

- **Adverbs of place**

Adverbs of place show the place where the action takes place. The following are the words that can be used as adverb of place in Afaan Oromo. '*as'* (here), '*achi'* (there),'*gadi'* (below), *gubbaa* (above), *jidduu* (middle), *irra* (on), etc. keessa (inside), *gala*, *jala* (under), *gubbaa* (top), *fuuldura* (infront), *duuba* (behind), *irra* (on), *maddii*, *bira*, *cinaa*(beside/near). Consider this example: *Caaltuun muka jala jirti* (Caaltuu is under the tree).

- **Adverb of manner**

Adverb of manner show how the action of the sentence is done. The following are Afaan Oromo words that can be used as adverb of manner *ariitin* (quickly), *suuta* (slowly), *akka gaarii* (well) etc. Consider the following example: *Har'a aduun baay'ee ho'a* (today is very sunny). In the above sentences, the word '*baay'ee*' (very) shows adverbs of manner.

- **Adverbs of reason**

In Afaan Oromo adverbs of reason are used to answer the word why (*maaliif*). *Sababa na jaallattuuf Caaltuun natti herumte* (Caaltuu married me because she loved me).

VI. Preposition (*Maqduubee*)

A preposition in Afaan Oromo is equal to postposition in English. In Afaan Oromo preposition is placed after a noun or a noun phrase to show the relation of other words from which a sentence is made (Bekama, 2007). This word in English is placed before a noun phrase to show the same relation. A few prepositions precede the noun in a sentence, but most follow the noun. A preposition links a noun to an action (e.g., "go from there") or to another noun ("the pen on the table"). Oromo prepositions divide into two categories: true prepositions and postpositions, with true prepositions coming before the noun and postpositions coming after the noun they relate to. Some Common Prepositions are *gara* (towards), *eega*, *erga* (since, from, after), *haga*, *hanga* (until), *hamma* (up to, as much as), *akka* (like, as), *waa'ee* (about, in regard to). Postpositions: *ala* (out, outside), *bira* (beside, with, around), *booda* (after), *cinaa* (beside, near, next to), *irra* (on), *irraa* (from), *itti* (to, at, in), *jala* (under, beneath), *jidduu* (middle, between), *keessa* (in, inside), *malee* (without, except), *wajjin* (with, together), *gubbaa* (on, above), *fuuldura* (in front of), *gad*i (down, below), *oli* (up, above). Consider the following Examples:

- ✓ *Tolaan akka fardaa fiiga* (Tola run like a horse).
- ✓ *Abdiisaan gara shaambuu deeme* (Abdisa goes to shambu).

In the above two examples the word *gara* and *akka* is a preposition.

VII. Conjunction (*Qarqabduu*)

A conjunction is a word used for joining words, phrases, clauses, and sentences (Bekama, 2007). There are many conjunctions in Afaan Oromo such as *fi* (and), *kanaafi* (for), *kana callaami* or *yookin* (not only), *lamaanirra tokko* (either..or), *ka gama lachuu hin tahin* (neither…or), *hatahuyyumalee*/Garuu (but), *hanga ammaatti* (yet), *lachuu* (both), *lachuu* (and), *yookin* (nor), *lameenirra tokkolle* (neither), *ti, si yookiin* (ykn), *yookaan* (ykn), *yoo, malee, illee, ammo,garuu ammoo, moo, hallettuu, garuu, qofa,qullii,idda, manna, akkasumas, kanamalees,hata'u malee, kanaaf, kanaafuu,ta'ullee,* and etc. are used.

VIII. Interjection (*Dinqiffannoo*)

Interjections are only the sound expressing the feelings of the speakers such as surprise, anger, regret, joy etc. (Bekama, 2007). Examples:

- ✓ *Attaam Ajaa'iba!* (What a surprising!)
- ✓ *Sodaachisaa dha!* (Terrible!)

2.9.5. Afaan Oromo Numbers

Two types of numbers are used in Afaan Oromo, cardinal and ordinal numbers. Oromo cardinal numbers refer to the counting numbers, because they show quantity. For example: *Afaan lama nan dubbadha* (I speak two languages). Some of the cardinal numerals in Afaan Oromo are *tokko* (one), *lama* (two), *kudhan* (ten), *dhibba* (hundreds), *kuma* (thousands), etc. Ordinal numbers on the other hand tell the order of things and their rank. Some of ordinal numbers in Afaan Oromo are *tokkoffaa (*First*)*, l*ammaffaa (*second*)*, *kurnaffaa* (tenth), *dhibbaffaa* (hudreth). Consider the following Examples:

- ✓ *Caalaan daree isaatii tokkoffaa bahe (*Caalaa stood first from his classes.)
- ✓ *Nama isa lammaffaa olgalchi* (let him get in the second man)

In the above two examples the word *tokkoffaa* is used to show a rank in the first example and the word *lammaffaa* is used to illustrate order in the second example.

2.9.6. Afaan Oromo Punctuation Marks

Analysis of Afaan Oromo texts reveals that different punctuation marks follow the same punctuation pattern used in English and other languages that follow Latin writing system. The following are the most commonly used Afaan Oromo punctuation marks.

- **Full stop/Tuqaa yookaan qabxii/ (.) :** Mostly used to show the end of sentence. e.g. *Chokoleetii baayyeen jaaladha* (I love chocolate very much). It also used in abbreviations e.g *Lakkoofsa Sanduuqa Poostaa* = L.S.P (abbreviation), in acronym's e.g. *Lakkoofsa = Lakk.* (Accronmy), to show decimals e.g. 2.5 cm = (decimal number). Further, it is used to differentiate the topic from its sub topics. For example:

  1. *Seenaa Oromo* = (Topic and its sub topics)

     1.1.Seenaa Gadaa

     1.2.Seenaa Ummataa

- **Question mark/Mallattoo gaaffii/ (?):** In Afaan Oromo question mark used at the end of interrogative sentences. For example: *Gatiin isaa meeqa?* (How many cost it is?). In addition to this, it is used to express non-exact years. This is done by writing question mark inside a brace following the approximate year. For Example: *Taaddasaa Birruu Bara 1921 dhalatee Bara 1975 (?) du'e* [Taaddasaa Birruu was born in 1921, died in 1975(?)].
- **Comma/Qoodduu /(,):** Comma is used to separate listing in a sentence. For Example: *Tadesse, Elias,Tamirat fi Kaasahun Barsiisota Yunivarsiitii Haramaayaati* (Tadesse, Elias,Tamirat and Kaasahun are Haramaya University Lecturers).
- **Colon/Tuq-lamee/ (:):** Colon comes before the listings in a sentence e.g., *Barsiisonni Kutaa barnoota Kompiteer Sayinsii: Tadesse, Elias,Tamirat fi Kaasahun dha.*(Computer Science department teachers are:Tadesse, Elias,Tamirat and Kaasahun)**.** ,and used to separate minute and hour in a time, e.g., *Dareen sa'a 8:30 A.M irraatti eegala* (The class will start at 8:30 A.M.)
- **Exclamation mark (!):** Afaan Oromo exclamation mark is used at the end of command and exclamatory sentences.
- **Semicolon/Buufata xiqqaa/ (;):** This is used in between the sentences that has the similar structure, length and time to decrease this sentence into single sentence.
- **Hyphen/Sarara Xiqqaa/(-):** Hyphen is used to differentiate two sentences that used to form single word. For Example: *Lubbuu+Qabeessa= lubbu-qabeessa* (Living thing)

There are also another punctuation marks such as quotation marks/*mallattoo waraabbii*/ “ ” or ’ ’/, parentheses/*hammattuu*/(), and ellipsis/*Fuftuu*/---. These punctuation marks usage is the same to English.

2.9.7. Afaan Oromo Capitalization/Qub-guddeessa/

In Afaan Oromo capitalization used to show the start of the sentence and the line of the poems. Sometimes it is simple that to delimit the sentence using capital letter if only a single punctuation mark is placed before a capital letter in the paragraph.

2.9.8. Afaan Oromo Sentence

In Afaan Oromo, sentence is created from one or more words, phrase or clause. For English language, sentence is composed of word order in a form of Subject-Verb-Object, but Afaan Oromo follows Subject-Object-Verb (SOV) format (Mandefro, 2010). Sentence is formed by combining *gulummoo* (subject) +*ibsa-xumurtuu* (adverb) + *xumurtuu* (verb) + *ibsa- maqaa* (adjective) + *gocha-fudhataa* (object) together. Consider the following examples:

- ✓ *Innii fi isheen* (subject) *farda* (object) *waliin* (adverb) *koran* (verb).
- ✓ *Inni farda dotii yaabbata* (He rides a gray horse)
- ✓ *Damma adii nyaachuu baayyeen jaalladha* (I like eating white honey).

Afaan oromo is a declined language (nouns change depending on their role in the sentence), word order can be flexible, though verbs always come after their subjects and objects. Typically, indirect objects follow direct objects. According to their function Afaan Oromo sentences are classified into four (Getaachoo, 2007). These are statement (*himaamsa/addeessa*), introgative (*gaaffii*), imperative (*ajaja*), and exclamatory (*raajeffannoo*). Statements are sentences that give facts, or describe event or what happened and they can be categorized as affirmative and negative. Afaan Oromo negative sentences are made by using negative markers such *as hin, miti, baat* (not).consider the following examples.

- ✓ *Tekinoon bilibila gaarii miti* (Techno is not a good phone)
- ✓ *Si hin jaaladhu* (I do not like you)
- ✓ *Yoo rafuu baatte nii dadhabda* (you will be exhausted if you don’t sleep)

In addition to these negative markers, in Afaan Oromo, if negative word is followed by a positive word it give a negative sentence and if negative word is followed a negative word it give positive sentence. Look at the following examples.

- ✓ *Bulchinsi Naannoo Harari bareedaa* (positive) *miti* (negative) (Harari Regional state governance is not good),
- ✓ *Tajaajilli hospitala Hiwot Faanaa yaraa* (negative) *miti* (negative) (Hiwot Fana hospital service is Not bad).

In addition to this categorization depending on the grammatical rule, Afaan Oromo sentence can be made in three forms. The first sentence formation is simple sentence that contains only one verb and says one thing about the subject. The second sentence structure is compound sentence that is formed from two or more simple sentences by using conjunctions. The third sentence formation is complex sentence that has one main clause and one or more subordinate clause.

2.9.9. Afaan Oromo and Sentiment Analysis

The rise of web content has presented a great opportunity to extract sentiment of people from social media. Not only for English language, the Latin Scripting language like Afaan Oromo has extensive amount of sentiment texts over the web which has to be extracted and interpreted for further understanding of people's opinions in some specific area. As it is expressed in the above sub topics Afaan Oromo has multiple features that used to express the polarity of something. For example: negative polarity is expressed using some words such as *hin*, *miti*, *baat* (not), and by writing negative sentence followed by positive sentence. In other hand, positive polarity is identified by considering subjective elements of the sentence and by writing two negative words consequently. In Afaan Oromo, polarity may be expressed by using the nouns, adjectives, verbs, adverbs etc. Adverbs are used to express the multi-class of sentiment by following nouns, adjectives or verbs.

In order to develop the accurate sentiment analysis for Afaan Oromo language it is significant to incorporate this feature. The Punctuation marks in this language are used for different purposes, though in order to use the punctuation marks for sentence delimitation the best mechanism should be developed. From types of Afaan Oromo sentence statement and exclamatory sentences are useful for sentiment analysis task. In addition to this, Afaan Oromo also has complex morphological information, which is very difficult to process. Whenever a large amount of Afaan

Oromo texts is there on the social media, there is no Afaan Oromo corpus that are used for sentiment analysis. The challenge that will be faced in this paper regarding the Afaan Oromo language is about preparation of sentiment corpus by understanding all the polarity features of the language.

2.10. Related Works

In this section, related sentiment analysis researches conducted for English, Non-English and Afaan Oromo languages using different approaches are discussed. In addition to the approaches, the language used, source of the data, procedures, experimental results, performance, and challenges of different sentiment analysis researches are considered.

2.10.1. Sentiment Analysis for English Texts

Pang *et al.* (2008) used machine learning approach for classifying movie reviews data into positive or negative sentiment. The author's approach consists of text preparation, text preprocessing, feature selection and sentiment classification with the help of three machine learning techniques: NB, SVM and MaxEnt. For experimental purpose 700 positive-sentiment and 700 negative-sentiment documents are used. Features such as N-grams (unigrams and bigrams), POS, feature frequency vs. presence, subjectivity (adjectives) and position of word are used to extract the important pattern for classifying data into their sentiment. The experimental result of this research indicates that, the accuracy of the sentiment classification using the SVM algorithm with unigram feature can achieve an accuracy of 82.9%, although the accuracy differences between those three algorithms aren't very large.

Additionally, Jain and Sharma (2018) developed classification of twitter data in multiple classes based on sentiment class labels. The researcher's contribution consists many steps like data set preparation, data preprocessing, negation filtering, tagging, classification and prediction. In order to identify the NLP features the POS tagging on data is performed and based on part of speech information the data is transformed into two dimensional vector. This two-dimentional vector is used with the SVM classifier for training and testing of implemented method. The result indicates that, the great accuracy (90-95%) when the as the training set is increasing from 800-1000 sentence.

Bordoloi and Biswas (2018) developed sentiment analysis of product using machine learning technique to compare three machine learning approaches: NB, SVM and MaxEnt. This study consists four stages: data collection, preprocessing, feature vector extraction and classification.

From the study experimental results it is observed that NB classifier has produced better performance(accuracy of 81.33%) than SVM (78.67 accuracy)and MaxEnt classifiers (76.47% accuracy) by using uigram feature.

Another more recent study of sentiment analysis is product reviews sentiment analysis that is undertaken by Jagdale *et al. (*2019) using machine learning techniques. In this paper, Dataset has taken from Amazon. Preprocessing and classification task are performed in this study. This paper concludes that, machine learning techniques gives best results to classify the Products Reviews. NB got accuracy 98.17% and SVM got accuracy 93.54% for Camera Reviews.

2.10.2. Sentiment Analysis for Non-English Texts

Waltinger (2010) tried an empirical study on machine learning-based sentiment classification using polarity clues for German language. The German 1000 corpus are used. All textual data (term features in the document) were passed through a pre-processing component, that is lemmatized and tagged by a POS-Tagger. The paper conclude, that combining a polarity-based feature selection with machine learning, SVMs using Linear-Kernel exhibit the best performance (accuracy of 84.1%).

Sentiment analysis system for movie review in Bahasa Indonesia using naive bayes classifier method is created Nurdiansyah *et al.* (2018). Movie reviews: 783 positive reviews and 418 negative reviews used for machine learning classifier. Naive Bayes machine learning classifier method is adopted in order to classify the sentiment. In the result, the highest accuracy is obtained when the dataset used consists of 1,000 review of training data and 201-test data review and the percentage is 90.05%. The paper, ended by discussing accuracy value is directly proportional to the number of reviews used as the dataset.

Wondwosssen and Wondwossen (2014) present a multi-scale sentiment analysis model for Amharic using supervised machine learning approach. This study contains various components such as Preparation of Corpus (600 posts collected), Annotation of Corpus, Lemmatization and Model Learning. Naïve Bayes machine learning algorithm employed and used unigram, bigram and hybrid variants as features. Generally, the results are encouraging about 44.3% using bigram feature despite the morphological challenge in Amharic, the data cleanness and small size of data. The drawback of the research is it consider small amount of corpus.

2.10.3. Sentiment Analysis for Afaan Oromo Texts

Eshetu Gusare developed Sentiment Analysis for Opinionated Afaan Oromo texts using lexicon approaches (Eshetu, 2017). In order to categorize the sentiment in to their polarity level the study constructed rules and used subjectivity lexicon of the language. The Afaan Oromo sentiment analysis model that is proposed in this paper involves of nine basic components. These are: texts preprocessing, morphological analysis, grammar checking, sentiment terms detection, ambiguity detection, polarity propagation, review's polarity weight calculation, review"s polarity classification and the developed subjectivity lexicon of Afaan Oromo language. In the preprocessing stage that discussed in this paper includes normalization and tokenization sub components. According to Eshetus, normalization is the process of transforming review texts into a single canonical form. In this work, for normalization task lower casing is used. The second preprocessing component that used in this work is tokenization that used to split the electronic Afaan Oromo texts into their token or words using space or newline. Natural language toolkit (NLTK) tool used to do tokenization. The morphological analyzer module accepts the preprocessed text and decomposes them into their root words and morphemes from the developed lexicon. The morphemes considers the derivational and inflectional property of Afaan Oromo language. By checking the presence of root words and morpheme in the sentiment lexicon, the morphological analysis sends the root words of the preprocessed terms to the grammar-checking component for grammar error inspection.

The other important components of this research work is sentiment terms detection. This component is responsible for finding and identifying subjectivity terms of a review from the developed lexicon of Afaan Oromo sentiment terms. This is done by a modest recognition technique where the whole lexicon is scanned for every term of a review. If the terms are exist in lexicon of Afaan Oromo sentiment then the polarity is assigned to the terms and send to the ambiguity detector component. This component receives the detected and reassigned sentiment terms of a review from the sentiment terms detection and these received sentiment terms of a review are redetected for ambiguity. To do that, context dependent terms of Afaan Oromo for sentiment analysis are collected and built within the developed lexicon of sentiment terms. Accordingly, before sentiment term's polarity value is propagated, the ambiguity detection is done, making sure that whether the detected sentiment term of a review is preceded by a context dependent term or not.

The rest of three modules that are included under polarity computation module are polarity propagation, review's polarity weight calculation and review's polarity classification. The polarity propagation module checks for contextual valence shifter term which is used for modifying the actual polarity values of a sentiment term within a given review. The polarity propagation is done considering whether the subjectivity term of a review is preceded or followed by the contextual valence shifter term (negation or intensifier) which is used for modifying the actual polarity values of a sentiment term within a given review. If a contextual valence shifter exist nearby sentiment term polarity propagation perform its tasks either to (negate, increase by 1 or decrease by 1) the polarity weight of detected sentiment term. Then the polarity weight calculation module use the values of the sentiment terms of the review and compute polarity values of each sentiment terms. To get the total polarity weight of the review each sentiment term values are added together. Finally, the polarity classification module use the total polarity weight and classify the review to the predefined categories of: positive and further classified as: (strongly positive, weakly positive), negative and further classified as: (strongly negative, weakly negative) or neutral by the polarity classification component. This way of categorizing sentiment is significant because it handles the fine-grained sentiment analysis, which does the multi-class sentiment analysis that used to understand the deep polarity of the review. In the experimentation of the research sentiment term collection and sentiment data collection is done. The sentiment terms are identified by considering subjectivity, POS and contextual valence shifter, these feature selection method is not enough to handle *Afaan Oromo* multi-class sentiment analysis. For example consider the sentiment "*Baayyee Gaarii*"(Very Good). This is formed from adverb ("*Baayyee*") and adjective ("*Gaarii*"). So, in addition to noun and adjective adverb has to be considered. Around 375 sentiment review are collected and used for lexicon preparation. The result of this experiment is calculated using precision, recall and f-measure and the maximum result achieved for precision, recall and F-Measure are 0.745, 0.890 and 0.718 respectively. The results indicates that study is promising. Even though the research achieved good result, it is not scalable because it use lexicon approach which are limited to small dictionary. In addition, the drawback the paper is it does not applied the preprocessing tasks which used to increase the sentiment pattern accuracy and it used small amount of feature selection methods which does not handle the whole Afaan Oromo sentiment formation.

The second work of Afaan Oromo sentiment analysis is contributed by Jemal Abate to analyze the Afaan Oromo political sentiments using opinion-mining technique by designing sentiment classification model (Jemal, 2018). The ideal of the research passed through collection of Afaan Oromo political sentiments, data pre-processing, POS-tagging, feature extraction and classification stages. Foremost, Afaan Oromo sentiments on political issue are collected political organization`s official website and Facebook page such as Oromo People Democratic Organization official Facebook page, political bloggers page such as: Jawar Mohammed, Ferhan Abduselam and Oromia Bloggers Network. After that, the preprocessing stage used. From the collected data about 600 Afaan Oromo review corpus are prepared. Next to data collection two preprocessing techniques are applied in this work which are tokenization and stop-word identification. Tokenization method that applied in this research used to chop texts into tokens, perhaps at the same time throw away certain characters, such as punctuation marks; so that texts within the collected reviews are tokenized into sentences, to facilitate POS tagging activity. In this study, the POS tagging activity for Afaan Oromo political sentiment is done by using HornMorpho tool. Following subjectivity detection by HornMorpho tool, the feature extraction is done. Because the HornMorpho tool assign noun to the subjective Afaan Oromo terms the POS tag that are assigned noun is extracted as a feature and used with little modification. At the final stage the research used the list of sentiment lexicon to classify the given sentence into the three polarity levels: positive, negative or neutral.

The classification activity is done by considering opinion shifter terms (negation). The experimentation was done using three features: unigram, bigram and trigram. Recall, precision and F-measure were the metrics used to evaluate the performance. The experimental result of unigram feature registered higher recall (73%) and bigram feature registered higher precision (82%) for both feature extraction and classification. The result shows that, the bigram model has good performance than that of trigram model and more informative than the unigram model. While the performance of this work is prominent, but it scored less performance than Eshetus work.

The tasks that are addressed by Eshetus but not performed by Jemal work are morphology analyzing, grammar checking and ambiguity detection. Eshetus classified the sentiment into multi-class: seven polarity levels while Jamel only classified it to three levels. In Eshetus, research total review classified into one of the sentiment classes. In reverse sentiment, classification is done on sentence level in Jemal research.

2.10.4. Summary

In the above sections, sentiment analysis research works for English, non-English and Afaan Oromo languages were reviewed. The review indicates that machine learning and lexicon based methods are the commonly used approaches for sentiment analysis task. The reviewed research work also showed that machine learning sentiment analysis approaches are based on the concept of training the machine to learn to classify sentiment texts into predefined categories of positive, negative or neutral or multi-class polarity levels. While the lexicon based approaches are based on the notion of counting the opinion words presented in the sentiment texts or documents. The result of the researches that are conducted using machine learning approach for both English and Non-English languages, excluding Afaan Oromo, attained high accuracy ranging from 80% to 99% by adopting machine learning algorithms such as: SVM,NB, and MaxEnt . The SVM performed better than NB and NB achieved better than MaxEnt. Although these results are promising one, the work are not directly applied for Afaan Oromo language because the grammatical structure and writing system of the language is different from English and non-English languages. Nevertheless, Afaan Oromo has multiple language feature that provide sentiment words and it is tried to incorporate these language features in this research work. In addition, two researchers Jemal and Eshetu attempt Afaan Oromo sentiment analysis task. In doing so, the researchers used rule-based approaches. Jemal research takes into account only three-polarity level. However, Eshetu research considered multi-scale sentiment analysis tasks, which is the strong side of this research. Both of the research is conducted on small sentiment lexicons which not scalable and the feature extraction method they used does not incorporate whole Afaan Oromo polarity words. Therefore, it is significant to apply the methodology that are adopted in non-Oromo languages. The other difficulty the review revealed is there is no Afaan Oromo sentiment corpus that aid to train the machine learning algorithms.

In order to figure out the gaps stated in the above reviews, the researcher developed Afaan Oromo multi-scale sentiment analysis based on machine learning approach using a supervised learning method. In doing to this, the challenges have been faced to process grammatical information of Afaan Oromo language for extracting whole features that give the sentiment words and to prepare the Afaan Oromo sentiment corpus that have been used for learning the machine. To the knowledge of the researchers, this is the first research, which have been applied machine learning approach for Afaan Oromo multi-scale sentiment analysis.

3. RESEARCH METHODOLOGY

In order to realize the stated objective, different methodologies and tools are applied. These are literature review, data collection, data cleaning, design and development techniques, development tools and performance evaluation.

3.1. Literature Review

Many literatures such as journals, papers, books of NLP and thesis papers (published and unpublished) are reviewed to understand how multi scale sentiment analysis techniques apply on internet data. Specially, literatures in the areas of sentiment analysis, sentiment analyzers models, Afaan Oromo language structure and characteristics, machine learning text classification approaches and algorithms, stemming and lemmatization, and supervised sentiment analysis on different language are reviewed. In addition, different videos, books and notes are reviewed to understand the general sentiment analysis and multi scale sentiment analysis. Evaluating all these literatures, the gap of previous research identified and a good approach nominated for multi scale sentiment analysis of Afaan Oromo posts.

3.2. Afaan Oromo Data Collection and Corpus Preparation Method

Corpus is a large and structured set of any text document. Supervised machine learning for NLP like sentiment analysis need annotated corpus to perform both training and testing tasks. Afaan Oromo is a resource poor language where there is no Afaan Oromo text corpus that is directly usable for the task of sentiment analysis. In this work, a corpus of 1000 sentences are collected manually by the researcher with the help of Afaan Oromo linguistic experts, from different Afaan Oromo sources such as social media sites, newspapers, sites, blogs etc. Afaan Oromo has rich sentiment texts on Facebook. Because of this, 600 sentences are collected from Facebook. The rest 400 sentences are prepared by collecting 50 sentences from eight sources: BBC (British Broadcasting Corporation) news Afaan Oromo, VOA (Voice of America) Afaan Oromo, OBN (Oromia Broadcasting Network) Afaan Oromo, OMN (Oromia Media Network) Afaan Oromo, Kichuu Info, Ayyaantuu News, Kallacha Oromiyaa newspaper and Afaan Oromo Bible. For the purpose of a uniform class distribution, the 1000 sentence corpus is folded into four equal size having 250 sentences for each polarity levels i.e., strong positive (250 sentences), positive (250 sentences), strong negative (250 sentences) and negative (250 sentences). There are no standard Afaan Oromo sites that collect people’s reviews. So, it is difficult to get the Afaan Oromo neutral sentiment data from the electronic posts. Not only in the language which has scarce review websites, it is also very challenging to grasp the neutral reviews for the language that has review websites (Abraham, 2014). To overcome this problem, the neutral polarity is identified during the classification stage by taking the features that are not found in either of positive class and negative class sentiment corpus. The other challenge of the Afaan Oromo posts are it include documents such as image, graphs, symbols, etc which are not filtered.

3.3. Data Cleaning/Filtering Method

The purpose of data cleaning is to remove noise, inconsistent data and errors in the training data. The social media text data include most noises such as symbols, pictures, graphs, tables etc. In this stage, the noises which do not exemplify the Afaan Oromo language feature and noises which are difficult to process with programming languages are cleaned manually to optimize the performance of the Afaan Oromo multi-scale sentiment analysis.

Following these manual cleaning, the experimental data preprocessing are employed to do tasks such as tokenization, normalization and stop word removal, which in turn increase the efficiency of the later classification tasks. Tokenization done to slice a sequence of character into the pieces, possibly discarding unnecessary characters, numbers, symbols etc. Even though there is no homophone characters in Afaan oromo language, the normalization is performed to normalize the word that are written in different style but have the same meaning into a single word form. The Afaan Oromo grammatical information that is not useful in the sentiment analysis task are considered as stop words and they are removed properly. The algorithms that were developed for exiperimental data preprocessing are explained in chapter 4 section 4.2.

3.4. Design and Development Techniques

The study applied design science research (DSR) methodology. Design science research, has been seen to constitute the third form of science "Artificial" in addition to the natural sciences and the human sciences (Alturki *et al.*, 2013). In addition, it seen as a research activity that build new or invents, innovate artifacts for problems solving or improvement attainment. Such new innovative artifact create a new reality, rather than the existing reality been explain or trying to make sense from it, it creates, and evaluates information technology artifact which is intended to solve some identified organizational problems (Alturki *et al.*, 2013). The design science research methodology has found a very good ground as a method in the Information Science and Computer Science, because it is a method that works with human, organizational social kind of problem solving through artifact development (Hevner R. *et al.*, 2004). Design science research includes five steps. These steps are Awareness of problem, suggestion, development, evaluation and conclusion. As a result, different mechanisms and development stages employed in developing Afaan Oromo multi-scale sentiment analysis for Afaan Oromo posts. The main activities involved in this work are proposal writing, designing multi-scale sentiemt analysis, developing prototype of multi-scale sentiment analysis, performance measures and discussion of the results. The tasks involved in design stage are preprocessing, morphological analysis, polarity assignment, feature extraction and representation, training machine learning algorithm and classifying the sentiment.

The system takes Afaan Oromo sentiment corpus as training data and take new data to predict the sentiment. In the preprocessing stage, noises of data are cleaned, the data are tokenized into a word for further processing, and heterogeneous writing style of the word are homogenized using normalization method. The main purpose of this stage is to optimize the prediction of machine learning model.

The second stage is corpus polarity assignment. Afaan Oromo linguistic experts perform this. First, the corpus are given to them in the text file, then after they categorize the text in to their polarity classes and save to as text file. Later the text file that saved according to their sentiment is loaded experimentally in format that best suits the machine learning algorithms.

The third phase is morphological analysis task, in which the two morphological analysis activities: POS tagging and stemming performed. First, Afaan Oromo POS tagger algorithm, which considers only the word categories that are used for sentiment analysis tasks such as adjectives, verb, noun, negation and adverb, is developed. In the same way, the POS tagging activity are performed by using HornMorpho tool. In the final process of POS stage, the tag identifier algorithm is developed which used to correct the HornMorpho tool output by using the output of Afaan Oromo POS tagger algorithm. Stemming are performed for the POS tagged features the corpus using the developed stemmer algorithm. For stemming purpose, the researcher with the aid of language exiperiments collects this, about 254 suffixs.

The fourth stage is feature extraction and representation, the important feature for sentiment analysis are identified and represented. In the sentiment analysis task the most important feature is the language part, which express polarity. In Afaan Oromo language, the polarity is expressed by adjectives, verbs that used as adjectives and nouns that used as adjectives. In other way, the negation is used to shift the polarity and the adverbs are used as intensifiers. In this study, the POS such as adjectives, nouns, verb, negations, and adverbs are taken as feature. Then, the extracted feature are represented using the BOW model, so that it is used in the training stage.

The final stage is training machine learning algorithms and performing multi-scale sentiment analysis. In many domains, former works has reported that the promising result is gained by using bag-of-word of POS as a feature and SVM, NB, and MaxEnt classifier algorithms for sentiment classification(Pang *et al.* (2008); Jain and Sharma (2018); Bordoloi and Biswas (2018); Jagdale *et al. (*2019) and Nurdiansyah *et al.* (2018)). So using this machine learning classification method is acceptable. In this stage, three supervised machine learning algorithms: SVM, NB, and MaxEnt is experimented using NLTK module. Initially, machine-learning classifier are trained on the entire corpus containing of subjective content that is used to train classifiers that can approximate the extent of sentiment content in retrieved documents. Afterward the classifier accepts a given post to classify it according to the classification knowledge acquired on training. At the end the polarity of the posts are calculate from one of five classes' (+2, +1,-2,-1 and 0) and the sentiment decision have been made depending on the outcome of the models. In order to test the proposed model, evaluation made on the prototype that are developed over these stages using accuracy, precision, recall and F-measure performance measures.

3.5. Development Tools

In order to achieve our objective the researchers used various environments and tools. Python 3.7.1 and an open source NLTK is used for implementation of preprocessing, lemmatization, training, classification and evaluation. Natural language toolkit is the most famous python NLP toolkit intended for helping with the entire NLP methodologies (Eshetu, 2017). The motive behind of using this programming language is it provides a suite of program modules, data sets and tutorials supporting research and teaching in computational linguistics and NLP (Steven Bird *et al.*, 2004). In addition to this, Python program language provide significant machine learning algorithm that used for text classification. HornMorpho 2.5 software that developed by (Gasser, 2012) is used for POS tagging. Notepad is used for corpus text operation and Microsoft word is used for writing report of the research.

3.6. Sentiment Classification Performance Evaluation

From the set of the corpus, 75% have been used for the training and 25% of the corpus have been used for testing purpose. The effectiveness of the sentiment classification is measured with methods, which compare the values of correctly, and incorrectly classified reviews. For this work, the standard classification accuracy measures: Accuracy, Precision, Recall and F- measures are used. The accuracy, precision, recall and f-measure metrics weigh the quality of algorithms separately for each class (e.g., more positive or positive). These metric is convenient for multiclass classification tasks to account for imbalanced test data (Vyrva, 2016).

Accuracy: It is one of the most common performance evaluation parameter and it is calculated as the ratio of number of correctly predicted reviews to the number of total number of reviews present in the corpus. The formula for calculating accuracy is given as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total}}$$

Precision: It gives the exactness of the classifier. It is the ratio of number of correctly predicted positive reviews to the total number of reviews predicted as positive. The formula for calculating precision is given in the following:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Recall: It measures the completeness of the classifier. It is the ratio of number of correctly predicted positive reviews to the actual number of positive reviews present in the corpus. The formula for calculating recall is given in the following:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

F-measure: It is the harmonic mean of precision and recall. F-measure can have best value as 1 and worst value as 0. The formula for calculating F-measure is presented as:

$$\text{F} - \text{Measure} = \frac{\text{2xPrecisionxRecall}}{\text{Precision} + \text{Recall}}$$

4. DESIGN OF MACHINE LEARNING BASED MULTI-SCALE SENTIMENT ANALYSIS FOR AFAAN OROMO POSTS

Sentiment analysis task can be done using either machine learning or lexicon method. In lexicon-based sentiment analysis, classification is done by matching the features of a given text along with lexicons whose sentiment values are stored. On other hand, machine learning sentiment analysis approach merely depends on text analysis and classification.Text analysis is mainly used for decision making, for which it require text preprocessing. This approach comprises two main steps: learning (training) and testing. Initially, the model trained using the polarity-annotated sentiment data. In multi-scale sentiment analysis polarity classes are classified as strong positive (+2), positive (+1), strong negative (-2), negative (-1) or neutral (0). Afterward in testing phase, the trained model predicts the unlabeled records by predicting their labeling class. Machine learning is a branch of AI that provides systems with the ability to automatically learn and improve from experience. Machine learning techniques further divided into two main approaches i.e. supervised learning and unsupervised (Pang *et al.*, 2002). In Supervised learning approach, algorithms learn from labelled examples and infer the label of new input based on the model built from the examples. For instance, in sentiment analysis task: the polarity of new input text is inferred from sentiment classifier model, which is developed based on polarity labelled data. In this work, a supervised learning approach that provides many algorithms for classifying text to its sentiments are used.

4.1. System Architecture

The general Architecture of the multi-scale sentiment analysis of Afaan Oromo posts is shown in Figure 4.1. As shown in the Figure, the system contains different steps and procedures in both training and prediction phase. These are *data collection*, *preprocessing*, *morphological analysis*, *corpus polarity assignment*, *feature extraction*, *training* a machine learning algorithm, and *classification.*

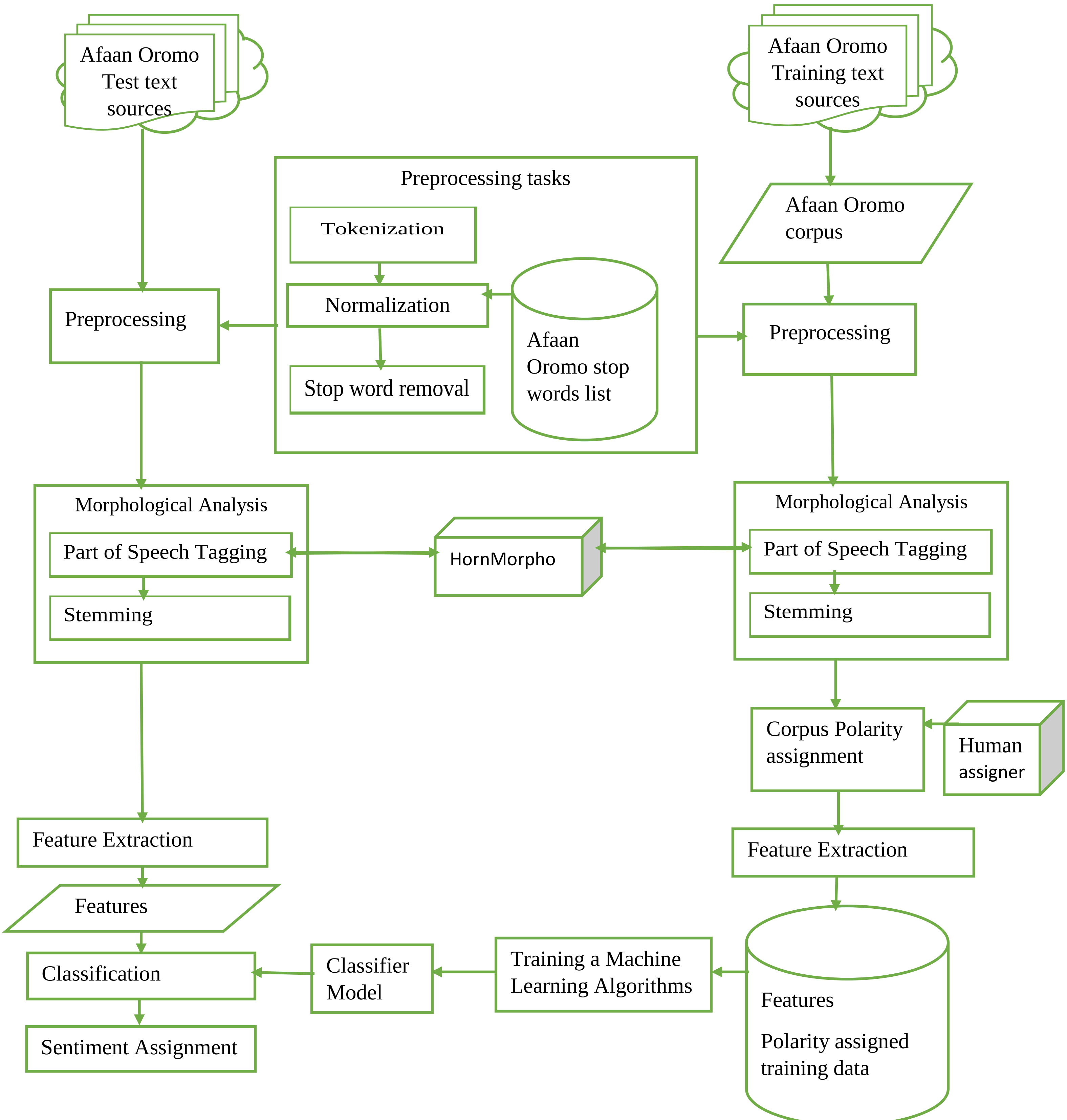

Figure 4. 1. Afaan Oromo Multi-Scale Sentiment Analysis System Architecture

4.2. Data Preprocessing

Preprocessing is a process of converting data to a format that is suitable for the learning task based on the selected machine learning method**.** Data preprocessing is the process of cleaning noises of data to make it easy for classification. This is done to improve the performance of machine learning real time sentiment classifiers. Social media data is usually inconsistent, incomplete, and lacking certain behaviors, and is likely to contain many mistakes. So, it is crucial to apply preprocessing task which resolve such problems. The preprocessing component of Afaan Oromo multi-scale sentiment analysis for Afaan Oromo posts comprises activities such as tokenization, normalization, and stop word removal. These processes are explained in detail in the following sections.

4.2.1. Tokenization

Tokenization is the process of splitting a string into list of pieces or tokens (words). A token is a section of a whole, so a word is a token in a sentence, and a sentence is a token in paragraph. Tokenization is done by detecting the boundary of the sentence or words. Like English language, Afaan Oromo uses punctuations as sentence delimiters and space for word demarcation. Punctuations like full stop (.), question mark (?), exclamation (!) are used as delimiters of sentence in Afaan Oromo. Not only for sentence demarcation, those delimiters used also for different purposes i.e. full stop is used for acronym, abbreviation, decimal number, topics and sub topics, and question mark is used to express non-exact years. So, an algorithm is developed to identify the purpose of the delimiters in paragraph. The developed tokenization algorithm is shown in figure 4.2. First, the collected data paragraphs are tokenized into sentence and the sentence is tokenized into words and stored separately to aid the other preprocessing tasks and morphological analysis tasks such as POS tagging, stemming etc.

In this stage, parallel to tokenization task, removal of special characters, symbols, numbers, punctuation and unnecessary spaces are performed. Special characters and symbols are signs that are not a letter, number, or punctuation mark. They do not exemplify the meaning by standing alone, rather they work with characters, numbers, and punctuations to transfer meaningful message. Like other Latin Script languages, Afaan Oromo has diacritics and symbols that are used for different purposes in writing the sentence. Some of the diacritics and symbols that are used in Afaan Oromo language are ampersand (&), *(asterisk), @(at sign) ,° (degree sign), $ (dollar sign), # (number or pound sign, or hash), % (percent), / (slash, solidus, stroke, or virgule), _ (underscore or understrike), !(exclamation), " (double quote), '(single quote), (left parenthesis,)right parenthesis), + (plus), .(full stop), -(minus), /(slash),<(lessthan), >(greater then), [(left bracket),](right bracket), ^(`(grave accent (backtick)), {(left brace), }(right brace) etc. First, the special characters and symbols are verified and listed. Then the removal of these characters and symbols are done by comparing the symbols in the input sentence or corpus with the list of characters and symbols prepared. Moreover, Afaan Oromo numbers, punctuations and unnecessary spaces are also other noises that are not significant for sentiment analysis. Punctuation marks of Afaan Oromo also less used in sentiment analysis task. After Tokenization takes place, no punctuations are necessary for doing sentiment analysis and they have been removed.

```
BEGIN
Open the corpus file or input sentence
While not end of corpus file or input sentence
DO
        For each punctuation mark in the corpus
                If the punctuation mark is in Afaan Oromo word delimiters
                        Put the words before the punctuation on a single line
                End if statement
                If special character is in the corpus or input sentence
                        Remove special character
                End if statement
                If symbol is in the corpus or input sentence
                        Remove symbol
                End if statement
                If number is in the corpus or input sentence
                        Remove number
                End if statement
                If punctuation mark is in the corpus or input sentence
                        Remove punctuation mark
                End if statement
                If unnecessary space is in the corpus or input sentence
                        Remove unnecessary space
                End if statement
        End for
End while
Close files
END
```

Figure 4. 2. Tokenization Algorithm

4.2.2. Normalization

Normalization is the process of converting texts into a single canonical form, which helps for further processing of text data in NLP. It is very useful for preprocessing text before search indexing, document classification, and text analysis. In sentiment analysis, normalization increase the computation of classification by performing activities such as word replacement: replacing the words that have similar meaning by a single word, case folding: converting case of the letter into either of lower case or upper case etc. Machine learning algorithms store words that has different format, size, spelling, cases etc., by dissimilar values that made the later sentiment classification difficult. To resolve this challenge, normalization activities such as word replacement and lower casing are performed in this work. Some of the Afaan Oromo words have the same meaning but they are written in different way. For Example, *baay`ee, baayyyee, baayyisee, baay`isee, baayyeetti*. Completely these words are converted to *baayyee* by word replacement method, for the reason of they all have the same meaning. Finally, case folding is performed to convert the corpus or input text to lower case.

```
BEGIN
Open tokenized corpus or tokenized input sentence
While not end of tokenized corpus or tokenized input sentence
DO
        For each character in the tokenized corpus or tokenized input sentence
                Convert character to lower case
        End of for
        For each lower cased word in tokenized corpus or tokenized input sentence
                If word has multiple writing style
                        Convert it to its identical form
                End of if statement
        End of for
Close tokenized corpus or tokenized input sentence
END
```

Figure 4. 3. Normalization Algorithm

4.2.3. Stop Word Removal

Stop words are words in natural language that are used as a function word for linguistics purpose and which does not have their own meaning. In addition, stop words usually occur frequently in the language text that do not contribute to the sentiment classification. In text semantic analysis tasks like sentiment analysis, the functional words that appear frequently should be removed, as they do not contribute in identifying emotion or opinion. Removing stop words help to convey clear meaning of the words for sentiment analysis task. Some of commonly used stop word classes in Afaan Oromo texts are pronouns (*maqdhaala*), prepositions (*maqduubee*), conjunctions (*qarqabduu*) etc. In order to remove those functional words, a list of Afaan Oromo stop words amounting about 300 are acquired from (Girma, 2012), (Nigussie, 2013), (Debela, 2010) and (Jemal, 2018) and 50 stop words are collected by the investigater with assistance of the Afaan Oromo linguistic experts. Totally 350 stop words are used for this study. Then, the stop words found in both Afaan Oromo training corpus and in the input text are removed by referring the stop word list. A stop word lists are attached in Appendix A.

```
BEGIN
Open normalized corpus or normalized input sentence
Open stop words list
While not end of normalized corpus or normalized input sentence
DO
        For each word in normalized corpus or input sentence
                If word not in stop word list
                        Store the word
                End of if statement
        End of for
Close normalized corpus or normalized input sentence
Close stop word list
END
```

Figure 4. 4. Stop word Removal Algorithm

4.3. Morphological Analysis

Morphological analysis is an area of linguistics that identify, analysis, and describe the internal structure of a given language's morphemes and other linguistic units, such as root words, affixes, parts of speech tagging, intonations and stresses, or implied context. A morpheme is the smallest meaningful unit of a given language e.g., token. Morphological analysis is very vital for various automatic NLP. In this work, POS and lemmatization/stemming morphology analysis tasks are performed using the output of HornMorpho morphilogical analyzer and POS tagger algorithm that are developed by researcher. HornMorpho is a system for morphological processing of Ahmaric, Oromo, and Tigrinya words into their basic words and generates words along with their grammatical category based on their morphology (Gasser, 2012).

4.3.1. Part of Speech Tagging

Part of speech tagging is process of classifying words into their parts of speech such as nouns, pronouns, prepositions, conjunctions, interjections, verbs, adjectives, adverbs and so on, and labelling them accordingly. Part of speech tagging is very useful for detecting the features and polarity words in sentiment analysis. According to the literatures, Afaan Oromo language has multiple word classes and each classes express different meaning. Word classes such as noun, verb, adverb and adjectives are used to show sentiments in different word structures.

In this work, HornMorpho tool is used for POS tagging. Even though the HornMorpho tool is used for Afaan Oromo POS, it does not give as accurate tag set for all Afaan Oromo words. In addition to this problem, one of the main problem in HornMorpho is that both noun and adjective is tagged as noun category (Jemal, 2018). To solve these challenges the researchers developed the POS tagger algorithm for Afaan Oromo language that considers adjectives, noun that used as adjective, verb that used as adjective, negation and adverbs. To find the adjective, negation and adverb part of speech, the algorithm that are developed by the researchers used gazetteers of Afaan Oromo adjectives amounting about 740, adverbs amounting about 125 and common Afaan Oromo negations indicators , which are prepared with the assistant Afaan Oromo linguistic experts. The sample of adjective gazetteers and adverb (intensifier) gazetteers are attached in appendix B and C respectively.

Besides, noun and verb POS tagging are done by using the affixes that used to form the adjectives from root/stem of nouns or from root/stem of verbs, and the affixes that used to produce verbs or nouns from root/stem of adjectives according to Afaan Oromo grammatical rule. These affixes are collected by the researchers during the literature review in the part of language feature and verified by Afaan Oromo linguistic experts. First, the file data are given to the HornMorpho tool, and the part of speech identified data are saved to text file. Then, the same file is given to part of speech tagger algorithm that developed for this work and the output of the tagger stored in the variable. Finally, to get the more accurate tag set, the output of HornMorpho and part of speech tagger algorithm are compared for each word tag in the input sentence, if output in the HorMorpho tool not similar with the output of part of speech tagger then the HornMorpho tag is replaced by part of speech tagger output. Thoroughly, the comparison and replacement of POS tag of Afaan Oromo POS tag and HornMorpho tag are done by tag identifier algorithm, so that precise tagging are made.

```
BEGIN
Open stop word removed corpus or stop word removed input sentence
While not end of file
        Input stop word removed corpus or stop word removed input sentence file to
        HornMorpho tool
        Save the output to posout text file
End of while
Close stop word removed corpus or stop word removed input sentence
END
```

Figure 4. 5. HornMorpho tool tagger

```
BEGIN
Open adjective list, adverb list, negation list, noun affix list, noun special case affix list, verb affix list, and verb special case affix list
Open stop word removed corpus or stop word removed input sentence
While not end of stop word removed corpus or stop word removed input sentence
DO
    For each word in the stop word removed corpus or stop word removed input sentence
        If word in adjective list
            Tag the word as adjective
        End of If statement
        Elif word in adverb list
            Tag the word as adverb
        End of elif statement
        Elif word in negation list
            Tag the word as negation
        End of elif statement
        Else extract word affix
            If word affix in noun affix list
                Tag the word as noun(noun used as adjective)
            End of If statement
            Elif word affix in noun special case affix list
                Tag the word as noun(noun used as adjective)
            End of elif statement
            Elif word affix in verb affix list
                Tag the word as verb (verb used as adjective)
            End of elif statement
            Elif word affix in verb special case affix list
                Tag the word as verb (verb used as adjective)
            End of elif statement
            Else
                Tag the word as default tag
            End of else
        End of else
        End of for
End of while
Close Files
END
```

Figure 4. 6. Afaan Oromo POS tagger algorithm

```
BEGIN
Open of HornMorpho posout file
Open output of Afaan Oromo POS tagger algorithm as aopos
While not end of posout file
DO
    For each word tag in posout file and aopos
    If word in aopos is tagged as adjective and word tag in posout is not adjective
        Replace the word tag in posout with adjective
    End of if statement
    Elif word in aopos is tagged as adverb and word tag in posout is not adverb
        Replace the word tag in posout with adverb
    End of elif statement
    Elif word in aopos is tagged as negation and word tag in posout is not negation
        Replace the word tag in posout with adverb
    End of elif statement
    Else
        If word in aopos is tagged as default
            Use posout word tagger as it is
    End of else
End of while
Close Files
END
```

Figure 4. 7. POS Tag Identifier algorithm

4.3.2. Stemming/Lemmatization

Afaan Oromo language has a complex morphology. It has affixes that change the meaning of the words and word classes. The stemming is done to reduce those inflected words to their stem or root, so that related words are mapped to the same stem. Stemming standardize different syntactical variants of a word to the main stem; this help to minimize the feature set in the documents and improve the performance of the sentiment classification models. For example, the word *bareeda* (beatiful) in Afaan Oromo may be written in different ways based on the context: *bareeddu*, *bareedditti*, *bareedaa*, *bareedoo*, *bareedoota*, *bareeddi*, *bareedolii* etc. These words have the same root called *bareed* and the underlined characters are the suffixes that used to inflect the words, so these has to stemmed to a single word *bareed* with help of stemming.

Some of Afaan Oromo nouns/ plural nouns that formed by attaching the consonant that found in the first syllable of the noun to the end of the first syllable and adding this to the original noun: Syllable-of-noun + consonant of first syllable of noun + original word of noun are used to express the sentiment. For example: *babbareeddu durba* (beautiful girls). In this example, the syllable bab- (s in English) is prefix and used as plural maker in the word *babbareeddu,* and the last syllable *du* is used to indicate that the word is verb. However, the only root or stem needed from this word is *bareed*. To overcome such issues, the researcher developed stemming algorithm that takes into account the affixes (prefix and suffix). The negation and adverbs word categories that used in this research has specific in number and they have the same writing format in overall the corpus. Because of this stemming are made only for the word categories such that adjectives, noun which are used as adjectives (intensifiers) and verbs that are used as adjectives.

In this study, for stemming purpose prefix and affix morphemes are considered. The prefix stemming done by seeing the syllable properties discussed above. While the suffix stemming is performed using the list of 254 suffix which are prepared with the assistance of language experts. Some of the suffixs are *u*, *itti*, *aa*, *oo*, *oota*, *di*, *olii, ummaa,* *ota*, *oolee*, *wwan*, *di*, *iinsa,* *uumsa*,*na*, *nu*, *eenya*,*amaa*, *oomii* *amani*, *amanii*, *ame*, *amniamu*, *amtu*, *amtani*, *amuu*, *omuu*, *oomi*, *oomuu*, *oomsuu*, *oolii*, *oolee*, *tti*, *rraa*, *ummaa*, *ooma*, *ittii*, *icha*, *ina*, *eenya*, *maata* etc. The list of suffix that used for stemming in this study is given in Appendix D.

```
BEGIN
Open part of speech tagged corpus, negation list and intensifier list or input sentence
While not end of part of speech tagged corpus file or input sentence
DO
        For each word in the corpus
                If word starts with a prefix
                        If word is not in negation and intensifier list
                                Remove prefix
                        End of if statement
                End of if statement
                If word ends with suffix
                        If word is not in negation and intensifier list
                                Remove suffix
                        End of If statement
                End of if statement
End of while
Close part of speech tagged corpus, negation and intensifier or input sentence
END
```

Figure 4. 8. Stemmer Algorithm

4.4. Afaan Oromo Corpus Polarity Assignment

Supervised machine learning classifier are built based on training corpora containing the correct label for each input. Fine-grained sentiment analysis that label the corpus with multi-polarity level is appropriate to study the polarity strength of the language, so that natural language has different polarity levels that exemplify the degree of sentiment. Although the three polarity levels are used more often to understand the polarity level, the multi-scale sentiment analysis address the whole sentiment of the people and rank the sentiment according to their granularity. In this work, multi level sentiment assignment is attempted and the corpus is annotated according to their sentiment polarity (either positive or negative) and strength using four sentiment polarity scales. Those sentiment polarity scales represented by +2 and +1 for the extent of more positive and less positive respectively, -2 and -1 for the extent of more negative and less negative, and 0 for the neutral sentiment. The sentiment polarity assignment on the corpus is done with the assistance of Afaan Oromo language experts. The collected data is provided to the experts with proper briefing and the data is manually identified whether it is positive or negative with their strength of polarity and encoded accordingly.

4.5. Feature Extraction and Representation

A feature is a portion of data that can be used as a characteristic of the object that can support in the process of prediction. Feature extraction is a process of eliminating features with no predictive information and determining subset of a feature set which is suitable and profitable for the classifier. In classification tasks, features that best describe data are essential for effectiveness and accuracy of machine learning algorithm. In sentiment analysis context, the features that express the sentiment are vital and have to identified and codified very well. Thus, in this work, after gathering useful information and preprocessing task are accomplished, feature extraction is done. The feature extraction task is done for both training and testing data which helps to make consistent pattern for prediction. The words which are lemmatized and classified according to their POS in the morphological analyser module, are used as feature in this stage. From part of speech, five word categories that are tagged as nouns, verbs, adverbs, adjectives and negations are extracted and n-gram of these tags used as a feature in this stage. These five features are significant to create multi-scale sentiment of Afaan Oromo language that is further analysed. In addition to this, the words tag that are already strong negative or strong positive is taken as a feature. Handling negation in text can also improve the accuracy of the classifier. The words that are tagged as negation in the POS tagging stage is used as the negation feature. Afaan Oromo negations may reverse the polarity of sentence by preceding and following other polarized word classes. The following examples shows some of the Afaan Oromo negation forms which reverse the polarity of the sentence.

- ✓ *Gaarii miti*
- ✓ *Hin bareedu*

In the first example, *miti* (not) is negation, in the second example, hin (not) is negation where as gaarii (good), and *bareedu* (beatiful) is positive words.

In Other hand, N-gram feature is a set of consecutive words found in a corpus, which express meaningful fragment of a sentence. An n-gram could be any combination of letters such as syllables, letters, word, POS, character, syntactic, and semantic n-grams. N-gram features provide the ability to identify n-word expressions (e.g., "*baayyee baayyee jaallatama dha*") (very lovely) which are used to capture multi-scale sentiment cues in text. This N-gram may be a negation word. The previous works achieved a promising result using unigram as feature (Pang *et al.,* (2008) ;Bordoloi and Biswas (2018); Jagdale *et al.,* (2019) and Abraham(2014)). In unigram features each word in the sentence represent a gram (single letter or single word). In Afaan Oromo, there is a probability that a single word is used to express polarity of the sentence, so unigram is one of the typical feature for sentiment analysis. In unigram, each word of the sentence is represented as a feature vector and the input word vector is compared with previously stored vector using machine learning algorithms to predict the polarity levels. In addition to the above features, a unigram feature of all words are explored for the classifier under this study. After important features are extracted, the text data is represented in a form that suit the selected classifier algorithms. In this study, N-gram feature (unigram) of all words that identified in POS tagging stage are represented using BOW model. The BOW model is commonly used in methods of document classification where the (frequency of) occurrence of each word is used as a feature for training a classifier (Mc Tear *et al.,* 2016). Also, BOW has been used by commercial analytics products including Clarabridge, Radian 6 and others. The NLTK classifier expects *dict* style feature sets, so the output text must be transformed into a dict (Abraham, 2014). In this study, each polarity assigned sentence is represented in dictionary format using BOW model. Later these features are given to the machine learning classifier to make the classifier model.

```
BEGIN
Open morphology analyzed corpus or input sentence
While not end of morphology analyzed corpus
DO
        Extract as a feature stem of words that are tagged as noun, adjective, verb, and adverb and
        negation
End of while
Close morphology analyzed corpus or input sentence
END
```

Figure 4. 9. Feature Extraction Algorithm

4.6. Training a Machine Learning Algorithms

The supervised machine learning algorithms are used for training the machine learning algorithms. In this approach, the classification model is developed on some set of a representative training documents.After accepting the data, the algorithm decides which label should be given to new data based on pattern and associating the patterns to the unlabeled new data. According to work of ((Pang *et al.,* (2002); Jain and Sharma (2018) ; Bordoloi and Biswas (2018) and Jagdale *et al.,* (2019)), the SVM, NB, MaxEnt machine learning algorithms are found to perform better for sentiment analysis. Having this indication, it is preferred to use these two algorithms for Afaan Oromo sentiment classification. First, polarity assigned sentiment data are trained with the machine learning algorithm and the new input text are predicted based on the training model. The working methods of the three supervised machine-learning algorithms, NB, SVM and MaxEnt, explained in the following section.

A. Naïve Bayes Classification

Naive Bayes is an approach to text classification that assigns the class $c^* = \text{argmax}_c P(c \mid d)$, to a given document *d*. It is based on Bayes' probability theorem and predominantly used when the dimensionality of the inputs is high. A few examples are spam filtration, sentimental analysis, and classifying news articles. Its underlying probability model can be defined as an "independent feature model". The NB classifier uses the Bayes' rule.

$$P(c \mid d) = \frac{P(c)P(d \mid c)}{P(d)}$$

Where, *P (d)* plays no role in selecting c^*. To estimate the term $P(d \mid c)$, Naive Bayes decomposes it by assuming the f_i's are conditionally independent given d's class as in the following formula.

$$P_{NB}(c \mid d) = \frac{P(c)\left(\prod_{i=1}^{m} P(f_i \mid c)^{n_i(d)}\right)}{P(d)}$$

Where, m is the no of features and f_i is the feature vector. Consider a training method consisting of a relative-frequency estimation *P(c)* and $P(f_i \mid c)$. One of the advantages of the NB classifies is that it requires less training data to estimate the best option of parameter for classification in opinion mining. Naive Bayes is optimal for certain problem classes with highly dependent features (Domingos et al., 1997).

B. Support Vector Machine Classification

Support vector machine is a "supervised classification technique which is based on maximum margin linear discriminants" (Banitaan, 2010). The SVM uses a "kernel function approach to map an input feature space into a new space where the classes are linearly separable" (Banitaan, 2010). Support vector machine have been shown to be highly effective at text categorization, generally outperforming NB (Joachims, 1998). They are large-margin, rather than probabilistic, classifiers, in contrast to NB and MaxEnt. In the two-category case, the basic idea behind the training procedure is to find a maximum margin hyperplane, represented by vector$\vec{w}$, that not only separates the document vectors in one class from those in the other, but for which the separation, or *margin*, is as large as possible. This corresponds to a constrained optimization problem; letting $c_j \in \{1, -1\}$ (corresponding to positive and negative) be the correct class of document *dj*, the solution can be written as in the following equation, w

$$\vec{w} := \sum_j \alpha_j c_j \vec{d}_j, \quad \alpha_j \geq 0$$

Where, the *αj*'s (Lagrangian multipliers) are obtained by solving a dual optimization problem. Those $\vec{d_j}$ such that *αj* is greater than zero are called *support vectors*, since they are the only document vectors contributing to$\vec{w}$. Classification of test instances consists simply of determining which side of $\vec{w}$'s hyperplane they fall on. The studies also show that SVM is effective, accurate, and can work well with small amount of training data (Lin and Ngo, 2007).

C. Maximum entropy Classification

MaximumEntropy classification is yet another technique, which has proven effective in a number of NLP applications (Berger *et al.*, 1996) show that it sometimes, it outperforms Naive Bayes at standard text classification. Its estimate Of *P(c | d)* takes the exponential form as expressed in the following formula.

$$P_{ME}(c \mid d) = \frac{1}{Z(d)} \exp\left(\sum_i \lambda_{i,c} F_{i,c}(d,c)\right)$$

Where, *Z (d)* is a normalization function. *Fi, c* is a feature/class function for feature fi and class *c*, as illustrated below.

$$F_{i,c}(d,c') = \begin{cases} 1 & n_i(d) > 0 \; and \; c' = c \\ 0 & otherwise \end{cases}$$

Importantly, unlike NB, MaxEnt makes no assumptions about the relationships between features and so might potentially perform better when conditional independence assumptions are not met. The λ_i,*c's* are feature-weight parameters; inspection of the definition of *P*ME shows that a large λ_i,*c* means that f_i is considered a strong indicator for class *c*.

4.7. Sentiment Classification

Sentiment classification is done automatically based on the sentiment classifier model that is developed by the selected learning methods. Given a text with possible sentiment, the classifier model classifies the sentence into either of five polarity levels: very positive (+2), positive (+1), Very negative (-2), negative (-1) and neutral (0). The result of the sentiment classification component sent to the result presentation module which display the sentiment reflected on the text to the users of the system in an understandable form.

4.8. Result Presentation /Sentiment Assignment

This module takes the value from both preprocessing module and from the classification module and finally display the result by sentence (polarity) format. For example if the sentence "Burtukaana nan *jaalla tokko naaf fidi"* (I love Orange bring me one) are first preprocessed and feed into the model, then the polarity level of this sentence is positive(+1) so the result is displayed on the prototype as *Burtukaana nan jaalla tokko naaf fidi (+1).*

5. EXPERIMENTATION AND PERFORMANCE EVALUATION

5.1. Introduction

As specified in the previous chapter, for conducting the exiperiment a corpus of 1000 sentences are collected manually by the researcher with the help of Afaan Oromo linguistic experts from different Afaan Oromo sources such as social media sites, newspapers, sites, blogs etc. After the data collection, preprocessing and important feature is extracted; the experimentation of the system is conducted using three supervised machine-learning algorithms: NB, Linear SVM and MaxEnt. The two machine-learning algorithms: NB, MaxEnt were used from NLTK module, and linear SVM was used from NLTK *SklearnClassifier* module. A common method in machine learning based sentiment or/text classification is to estimate the performance of the algorithms by splitting data sets into two: training data set and testing data set (Bird *et al.,* 2009). In this study, from each multi-scale class of the corpus, 75% is used for training and the rest 25% is used for testing purpose. To represent the extracted features text with machine learning algorithms the BOW model is used. The BOW model has seen great success in problems like language modeling, and document classification i.e. sentiment analysis (Pang *et al.* (2002); Padmaja and Fatima (2013); Jain and Sharma (2018) ; Bordoloi and Biswas (2018) and Jagdale et al. (2019)). In this model, a text (such as a sentence or a document) is represented as the bag (multiset) of its words. Because of small amount of corpus is used this is the preferable modelling for our experimentation.

This chapter presents the experimental results and evaluation of the developed prototype for machine learning based multi-scale sentiment analysis for Afaan Oromo posts. The experimentation and evaluation, discussion, and prototype are presented in the following sections.

5.2. Experimentation and Performance Evaluation

In this section, the applicability of applying machine learning algorithms for Afaan Oromo multi-scale sentiment analysis has been examined. As it is discussed earlier, the experimentation are performed on three machine learning algorithms: NB, SVM, MaxEnt, using BOW of extracted features as a model. Entire 1000 sentences were used for undertaking the experiments. Each corpus review is classified into their sentiment class using the developed prototype. To evaluate the effectiveness of the system accuracy, precision, recall, and F-measure metrics are used. The experimental setup, manual sentiment annotation and results acquired for three experiments are provided in the following sections.

5.2.1. Experiment setup

The experimentation has been done on a laptop PC with Windows 10 operating system, 2.30 GHz Intel CPU, 4 GB RAM and 500 GB hard disk. Notepad, Python 3.7.1 programming language and NLTK tool were installed and configured for the development and testing of the developed model.

5.2.2. Manual Corpus Sentiment Annotation

The sentiment corpus are annotated into their polarity classes by the Afaan Oromo linguistic experts into four categories: +2, +1,-2, and -1, where +2 stands for strong positive, +1 is stands for positive, -2 stands for strong negative and -1 stands for negative respectively. As a result, total of 1000 Afaan Oromo reviews are separated into four equal level yielding 250 reviews for each sentiment class and annotated according to their polarity value. The manually annotated reviews support in developing the sentiment classifier model and in validating the results gained from the proposed prototype of Afaan Oromo multi-scale sentiment analysis. The reviews manually annotated to their sentiment classes along with their quantities are presented in Table 5.1.

Polarity scales	**Manually classified reviews**
Strong Positive (+2)	250
Positive (+1)	250
Strong Negative (-2)	250
Negative (-1)	250
Total Reviews	**1000**

Table 5. 1. Manually annotated Afaan Oromo sentiment reviews

The corpus used is a balanced corpus where there are equal number of data in each class. This is important to avoid biasness during the training phase. A sample Strong positive, positive, strong negative and negative sentiment reviews is attached in Appendixes E, F, G and H respectively.

5.2.3. Experiment one: Using Naïve Bayes Algorithm

This is experimented using NB algorithm. Initially, *NaiveBayesClassifier* imported from nltk.classify module. Then, training data, which includes the feature and sentiment label is represented by BOW model. Following this *nltk.NaiveBayesClassifier.train()* class is called by passing the BOW data as a parameter. To measure the performance, precision, recall, accuracy, and f-measure are imported from *nltk.metrics*. To calculate each polarity class metrics the testing set features that labeled by sentiment class is passed as parameter to the class *classifier.classify(feats).* Feats contains BOW model of testset. Finally, NB algorithm results measured by accuracy, precision, recall and f-measure for each classes of polarity and the average of the evaluation result is taken to illustrate total system performance. The evaluation of results of experiment one is presented in table 5.2.

System	**Algorithm**	**Sentiment Classes**	**Evaluation Metrics**			
			Precision	**Recall**	**F-Measure**	**Accuracy**
Machine Learning Based Multi-Scale Sentiment Analysis for Afaan Posts	Naïve Bayes	Strong Positive(+2)	0.746	0.746	0.746	0.746
		Positive(+1)	0.714	0.635	0.672	
		Strong Negative(-2)	0.75	0.905	0.82	
		Negative(-1)	0.772	0.698	0.733	
Average			**0.745**	**0.746**	**0.743**	

Table 5. 2. Result of Experiment One: using NB algorithm

As the result presented in the Table 5.2 NB classifier achieve the overall accuracy of 74.6% for classifying Afaan Oromo multi-scale sentiment. For strong positive polarity classification, the classifier scored 74.6% for all evaluation metrics. This indicates that, the amounts of false positive, false negative, and average of both false negative and false positive that are caused in the strong positive classification is 25.4%. The NB classifier yields 71.4 % precision, 63.5% recall and 67.2% f-measure for positive class. For strong negative sentiment classes, by using the similar classifier the classification error is reduced to 25% in which 75% is correctly identified. This is the good precision when compared to the other sentiment classes: strong positive, positive. The recall and f-measure of the NB classifier for the strong negative class are 90% and 82% respectively. The result of strong negative classification shows that the number of false negative is decreased to 9.5% which is the smallest error rate from all sentiment classes.

Likewise, in negative class, the 77.2 % have been identified correctly and false positive value cease to 22.8 %, which is the highest precision, compared to the rest of sentiment classes. The recall for the class negative is 69.8%, and f-measure is 73.3%. In this sentiment class, the number of false negative and average measure of recall and precision is minimum next to positive classes.

Generally, the Average precision, recall, and f-measure that are gained by using NB classifier are 74.5, 74.6 and 74.3 respectively.

5.2.4. Experiment two: Using Support Vector Machine Algorithm

The second experiment was conducted using SVM algorithm. The SVM is exipermented by importing *SklearnClassifier* from *nltk.classify*. First the *classifier* is assigned *nltk.classify.SklearnClassifier (LinearSVC()).* After that *classifier.train ()* class is called by passing the same traing set that used in NB. The results of this experiment are evaluated with similar measurements methods that used in experiment one. Table 5.3 shows the evaluation results of experiment two.

System	**Algorithm**	**Sentiment Classes**	**Evaluation Metrics**			
			Precision	**Recall**	**F-Measure**	**Accuracy**
Machine Learning Based Multi-Scale Sentiment Analysis for Afaan Posts	Support Vector Machine	Strong Positive(+2)	0.857	0.762	0.807	0.73
		Positive(+1)	0.685	0.587	0.632	
		Strong Negative(-2)	0.791	0.841	0.815	
		Negative(-1)	0.613	0.73	0.667	
Average			**0.737**	**0.73**	**0.73**	

Table 5. 3. Shows result of experiment two: using SVM algorithm

Table 5.3 presents the accuracy, precision, recall and f-measure of the SVM classifier algorithm. The strong positive class yields precision 85.7%, which are considerably better than the results of the other SVM, and NB classified sentiments classes' precision. Support vector machine is effective, accurate, and can work well with small amount of training data (Tam, 2006). The reason strong class score a good result is the words that used in this class are identical, so that during training phase the SVM algorithm considers small amount of data. The number of false positive is reduced by 11.1% from the value of NB classified strong positive class, causing only 14.3% false positive. In the same manner, the recall and f-measure of the strong positive class raise to 76.2 % and 80.7 % respectively, this improves the NB algorithm strong positive class recall and precision. In positive class, about 68.5 % negative reviews are correctly identified. When we compare it with the NB positive class results the results of SVM for positive class is less i.e. precision 68.5 %, recall 58.7 %, and 63.2% f-measure. This result have been shown that, the positive classes are not more learned by SVM classifier. The strong negative category yield relatively high precision (79.1%), which improves the experiment one strong negative precision by 4.1 %. The recall

(84.1%) and f-measure (81.5%) is less than recall and f-measure of experiment one for strong negative classes, but they are much better than the recall and f-measure of all other experiment two sentiment classes. Moreover, the negative class score precision smaller than the rest of other sentiment classes. The negative class f-measure is 66.7percentage and the recall is 73%.

The average precision of SVM classier is 73.7%, while the average of accuracy, recall and f-measure metrics value achieved the identical result, which is 73%. Even though the average result of NB classifier is slightly higher than that of SVM classifier, the result is promising with small difference.

5.2.5. Experiment three: Using Maximum Entropy Algorithm

This is the last experiment conducted using MaxEnt. In this stage, *MaxentClassifier* is imported from *nltk.classify*. In addition, *MaxentClassifier.train()* class is called by passing the training set BOW model. The results of MaxEnt is evaluated using similar metrics and by following similar procedure of exiperiment one. Table 5.4 shows the evaluation results of experiment that are performed by MaxEnt.

System	Algorithm	Sentiment Classes	Evaluation Metrics			
			Precision	Recall	F-Measure	Accuracy
Machine Learning Based Multi-Scale Sentiment Analysis for Afaan Oromo Posts	Maximum Entropy	Strong Positive(+2)	0.662	0.683	0.672	0.639
		Positive(+1)	0.586	0.54	0.562	
		Strong Negative(-2)	0.746	0.698	0.721	
		Negative(-1	0.571	0.635	0.602	
Average			**0.641**	**0.639**	**0.639**	

Table 5. 4. Shows result of experiment three: using MaxEnt algorithm

As illustrated in Table 5.4, MaxEnt classifier result is poor when compared to the other two classifier: NB, SVM results. However, the strong negative class precision value of NB classifier and MaxEnt classifier is almost similar. The strong positive class attained 66.2% precision, 68.3% recall, and 67.2% f-measure. In addition, for the positive class 58.6% precision, 54% recall, and 56.2 f-measure have been achieved. The strong negative class results: precision (74.6%), recall (69.8%) and f-measure (72.1 %) are maximum when compared to all other sentiment class precision, recall and f-measure value. The negative class precision, recall, and f-measure value are

57.1%, 63.5%, and 60.2% respectively. Average precision of MaxEnt classifier is 64.1%, while overall accuracy, recall, and f-measure value performed 63.9%.

In order to investigate the relationship between performance and corpus size, the researchers collected 200 additional sentences and totally the system re-exiperimented using 1200 sentences by three algorithms. The result of the exiperiments are shown in Table 5.5.

System	Algorithm	Sentiment Classes	Evaluation Metrics			
			Precision	**Recall**	**F-Measure**	**Accuracy**
Machine Learning Based Multi-Scale Sentiment Analysis for Afaan Posts	Naïve Bayes	Strong Positive(+2)	0.716	0.84	0.773	**0.723**
		Positive(+1)	0.726	0.6	0.657	
		Strong Negative(-2)	0.691	0.893	0.779	
		Negative(-1)	0.792	0.56	0.656	
Average			**0.731**	**0.723**	**0.716**	
Machine Learning Based Multi-Scale Sentiment Analysis for Afaan Posts	Support Vector Machine	Strong Positive(+2)	**0.9**	0.84	0.869	**0.83**
		Positive(+1)	0.792	0.813	0.803	
		Strong Negative(-2)	0.868	0.88	0.874	
		Negative(-1)	0.766	0.787	0.776	
Average			**0.831**	**0.83**	**0.831**	
Machine Learning Based Multi-Scale Sentiment Analysis for Afaan Oromo Posts	Maximum Entropy	Strong Positive(+2)	0.69	0.773	0.73	**0.66**
		Positive(+1)	0.688	0.587	0.633	
		Strong Negative(-2)	0.647	0.733	0.688	
		Negative(-1	0.612	0.547	0.577	
Average			**0.659**	**0.66**	**0.657**	

Table 5. 5 Effect of Corpus Size on Performance Measures

The exiperiments shown in Table 5.5 shows that the accuracy increased for the two algorithms: SVM, MaxEnt. While the accuracy of the NB algorithm are ceases with a little difference. The precision of strong positive is very high scoring 90% for SVM algorithm.

5.3. Prototype

To show the system functionality the demo is developed by python programming tkinter module, which aid to develop a window-based graphical user interface. The demo allow the user to write the sentiment or/opinion sentence in Afaan Oromo through their terminal or computer and submit to get the polarity level of the sentence, so that the sentiment is preprocessed, morphologically analyzed, selective feature taken, classified and the polarity of sentence displayed. Sample of the prototype for strong positive sentence along with polarity have been presented in Figure 5.1. In order to run the prototype the user open *train.py* using IDLE (Integrated DeveLopment Environment) of Python 3.7.1. After the *train.py* opened, under run menu, the *Run Module* clicked or F5 pushed from the keyboard. As a result, the prototype displayed as shown in figure 5.1. In this prototype, three labels are used. These labels are *Yaada Keessan Galchaa* (Enter Your Opinion), *Bu`aa Yaadaa* (Sentiment Value) and *Algoorizimii Filadhaa* (Select Algorithm). Each algorithms represent the sentiment classification model. In addition to this, three buttons: *Qoqqodi* (Classify), *Haqi* (Clear) and *Cufi* (Close) are used. To process the sentiment of the text the user either type or copy the sentence to enter your opinion *text field*. Next, one of three-algorithm radio button is checked. Following this, the user click on *Qoqqodi* button. When *Qoqqodi* button is clicked the opinion text load into classification model of the selected algorithm. Finally, the system made prediction and result displayed on the *Bu`aa Yaadaa text field.* The result, which is displayed in this text field is one of the five sentiment class (+2, +1,-2,-1 and 0) with appropriate definition. The *Haqi* button used to clear both the *Bu`aa Yaadaa text field and Yaada Keessan Galchaa text area*. To close the prototype window the user click on the the *Cufi* button.

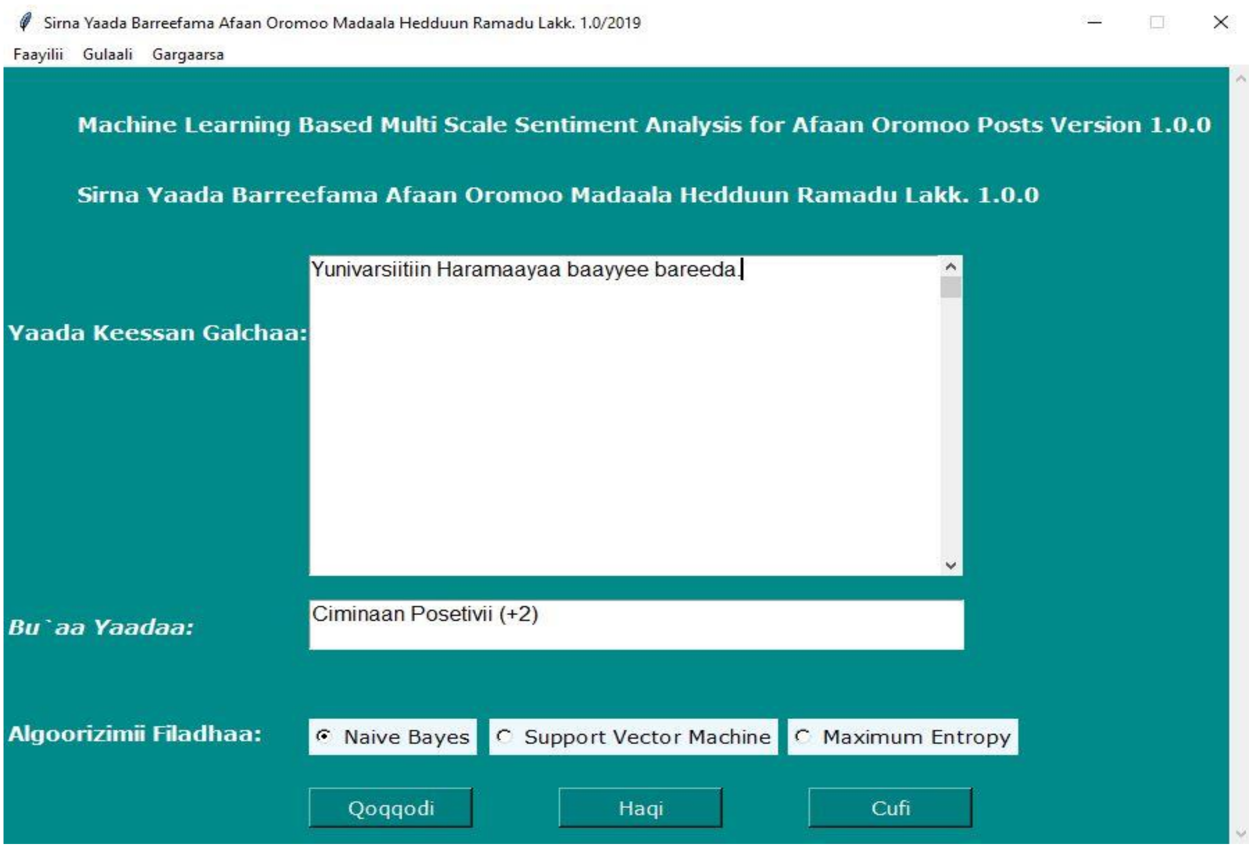

Figure 5. 1. Afaan Oromo sentiment texts entry interface with Strong positive review

5.4. Discussion

As presented the above, the experiments are performed using three different machine learning algorithms and the promising results were obtained for Afaan Oromo posts multi-scale sentiment analysis. The possible reason for variation of the results in each learning algorithm for each sentiment classes are argued in the following section.

In the three experiments, the study achieved the highest performance for both strong negative and strong positive sentiment datasets. This is due to the communality of words in these datasets. In the corpus, most of the words that are used to form either strong negative or strong positive sentence are similar to each other. So, the duplicated words are stored in the bag-of-word model which helps to enhance the machine learning algorithms prediction. In the other hand, precision of the strong negative exceeds that of strong positive in experiment one and three, however strong positive class scored greater in experiment two. The deviance of this precision value is caused because of the same Afaan Oromo intensifiers words that are used both for strong positive and strong negative. Consider the following two examples: *Baayyee gaarii* (very good), *Baayyee* *badaa* (very bad). In these examples, the word *baayyee* is used as intensifier. During the training phase, the word *baayyee* may found in the features of both strong positive and strong negative training sets. Hence, depending on the properties of the experiment algorithms the system precision may be up and down. Likewise, next to strong positive or strong negative datasets, the system performs well with positive sentiment class datasets than negative sentiment class datasets in all the above three experimental results. This is caused because of the complexity of morphological features of the language. In this study, some issues that makes the imprecise results of multi-scale sentiment analysis for Afaan Oromo language are investigated.The former cause is that when the reviews entered by the user has the names that has the sentiment. In this case, the proposed system may incorrectly classify the neutral sentiment to either of one classes. For example: in the review like: in the sentence "*Nyaanni kun kan Hootela Gammachuu ta`uu hin oolu*": positive (+1), the conveyed sentiment is neutral but the system classified it as positive. This is for the reason of the word *Gammachuu* (happiness) that used to express the hotel name.

The second reason for bias of result is the feature representation model (BOW) which does not consider position of the words rather it takes into account the frequency of words for each sentiment class. So that the review is categorized into the model of sentiment class which contains the high frequency of the words that found in the review. The similar words that found in each sentiment class model makes challenging the task of sentiment classification for learning algorithms. In addition to this issues, the negation that used to shift the polarity of each words are also diverge the results. For example: in the sentence "*hama miti*": positive (-1), is assigned negative polarity while it is positive sentiment. This is happened because of the feature representation methods of the system is not considered the negation positions but only terms are considered. However, the learning model of this system only considered the sentiment terms frequency. These types of sentence review can be managed by applying special negation handling mechanisms that are used in the work of (Das *et al.,* 2001; Pang *et al.,* 2002). Besides, the objective reviews that are stated as implied opinion and comparative opinion are not classified accurately by the system. Thus, the Afaan Oromo indirect expressions: *cigoo*, *qeeqa,* are not considered well by the system. These problems needs another investigation approaches that combine the implicit, explicit and comparative sentences in sentiment analysis. Most of the time the users comment on the social media by using identical Afaan Oromo words (e.g., *bareedaa*, *gaarii*, *hattuu etc*). As a result, the corpus prepared for this research may not incorporate all Afaan Oromo sentiment words.

Because of this, sometimes the system may not catalog the sentiment correctly. This problem is resolved if the Afaan Oromo standard sentiment corpus are prepared. In sentiment assignment, sub task the system does not extract the feature of the sentiment. This kind of task may need another task named co-reference resolution and later feature/aspect based sentiment analysis. Furthermore, the system delay to respond to the user input. This is because of the HornMorpho morphological analysis tool and NLTK module that used for learning. To overcome this problem fast and accurate Afaan Oromo morphological analyzer and learner algorithm has to be investigated. From overall experimental results presented above, it is perceived that NB classifier algorithm outdoes SVM and MaxEnt using all sentiment class datasets. In case of the performance of SVM and MaxEnt are compared, SVM is better than MaxEnt because SVM does better than MaxEnt in all datasets of sentiment classes: in experiment two. Taking in to account the results, the NB and SVM algorithms are far better than the MaxEnt algorithm in classifying Afaan Oromo multi-scale sentiment and for making predictions that are more accurate. In Table 5.2, 5.3, 5.4 and 5.5 it can be seen that three machine-learning classifiers yield relatively high accuracy (74.6%) using 1000 sentences and accuracy of 83.3% using 1200 sentences. The performance of SVM algorithm is better than NB for Afaan Oromo sentiment analysis task as the corpus size increase. Therefore, when the corpus size increase, the accuracy of the system also increase for SVM and MaxEnt algorithms, and the accuracy of NB algorithm decrease by small number.

Generally, the above experiments are investigated for first time by the researcher and the promising result is achieved. Accordingly, it can be encouraged that machine learning algorithms can be appropriate for doing social media posts multi-scale sentiment analysis in the low resourced language like Afaan Oromo. This research aimed to answer two research questions: RQ 1: Which feature of Afaan Oromo language is appropriate to express the sentiment intensifiers? RQ 2: How typical machine learning technique be applied to perform multi scale sentiment analysis of Afaan Oromo social media posts? Based on the study of Afaan Oromo language feature and morphological analysis made in this work the sentiment intensification expressed when noun, adjective or verb followed by adverb and when adjective, noun or verb that is followed by negation is followed by adverb, as a result the first research question (RQ1) is answered. The results indicates that using machine learning algorithms specially NB and SVM for multi-scale Afaan Oromo posts sentiment analaysis is encouraging, so this study resolved the second research question (RQ2).

6. CONCLUSION AND RECOMMENDATION

6.1. Conclusion

The recent rapid growth of the internet engenders it seem that the world is attesting the onset of an utterly fresh technology. In fact, the social media nowadays changes the way that people communicates their sentiment and or opinions. Now the people posts their views and opinions on the internet forums, discussion groups, blogs, and social media. These posts are important for identifying the opinions of the people regarding company, products, politics, consumer behavior, people, and other issues. For instance, sectors such as advertisers, movie creators, booksellers, political parties, supermarkets, industries, restaurants etc. demand their customers' feedback on a particular issue to improve themselves afterward. However, it is difficult for human to extract relevant sentences, categorize and present the internet posts in apprehensible and useful format. Therefore, automatic multi-scale sentiment assortment and cataloging systems are needed. The main goal of this study was to design and develop multi-scale sentiment analysis for Afaan Oromo.

Multi-scale sentiment analysis system is advanced to classify the sentiment of the Afaan Oromo internet posts into five polarity classes: strong positive, strong negative, positive, negative and nuetral. To categorize the Afaan Oromo sentence into their polarity levels the system performs activities such as preprocessing, morphological analysis, feature extraction and representation, training machine learning algorithm, classification and evaluation. Preprocessing comprises activities such as tokenization, normalization, and stop word removal. To perform stopword removal, a list of Afaan Oromo stop words amounting about 350 are identified and recorded with assistance of the Afaan Oromo linguistic experts. Morphological analysis is a process of identifying, analyzing, and describing the internal structure of a given languages. This stage involves POS tagging and stemming activities. The POS tagging process categorize the words to their part of speech class such as noun, verb, adjective, adverb, negation and stemming method provide the base forms of the POS tagged words. First, the POS tagging are done using HornMorpho tool. Then, the output of the HornMorpho tagger is corrected using Afaan Oromo part of speech tagger investigated in this system. To find the adjective, negation and adverb part of speech, the algorithm that are developed by the researchers used gazetteers of Afaan Oromo adjectives amounting about 740, adverbs amounting about 125 and common Afaan Oromo negations indicators , which are prepared with the assistant Afaan Oromo linguistic experts. The stemming are done using 254 suffixs. The feature extraction and representation module is accountable to extract the words that are lemmatized and tagged as adjective, noun, verb, adverb and negation. In addition, this module represent the features in dictionary format using BOW model. Training machine learning algorithm is concerned with training the machine learning algorithms depending on the human annotated sentiment data. For training purposes three machine learning algorithms: NB, SVM, and MaxEnt are used. According to the literature, these NB, SVM, and MaxEnt learning algorithms are scored the best accuracy in the classification of sentiment. Having this indication, these three algorithms are used for Afaan Oromo sentiment classification. In order to train the algorithms 1000 review posts are collected from the internet and annotated with into their polarity levels (+2, +1, -2, -1) by Afaan Oromo linguistic experts. So that there is no Afaan Oromo sentiment corpus before these is one of the major contribution of this work. The bag of stemmed sentiment annotated data are given to the three machine learning algorithms and three-sentiment classification model is developed. The classification stage of the research deals with sentiment classification that classify the users input to their sentiment depending on the models developed by the machine learning algorithms. To show the system functionality the demo is developed by python programming tkinter module which allows the user to input the new data. The reviews that provided by the user are classified to one of the sentiment level and the result is displayed back. To the level of researcher's knowledge, this is the first work for Afaan Oromo language multi-scale sentiment analysis that considered all morphology features and realized using machine learning method. Finally, the system is evaluated by splitting the sentiment corpus into training and testing sets. Many research works, use 75% of the review for training and 25% for testing. Due to this, from overall 1000 reviews 75% of the review used for training purpose and 25% is used for testing purpose. The performance of the machine learning based multi-scale sentiment analysis for Afaan Oromo posts model is encouraging achieving accuracy of 74.6%, 73% and 63.9% for NB, SVM and MaxEnt classifier using 1000 sentences. In other way, using 1200 sentences the system achieved accuracy of 72.3%, **83%** and 66% for NB, SVM and MaxEnt respectively. While these results verify the main contribution of the study, some factors make the sentiment classification task and reduced efficiency of the system. These factors may be the use of HornMorpho tool, negation representation problem, feature representation model (BOW) which consider only the frequency of words rather than their position in the sentence) and the use of small amount of corpus.

6.2. Recommendation

In this research, design and development of machine learning based multi-scale sentiment analysis for Afaan Oromo posts model is attempted. In general, the result obtained in this study has been encouraging. Developing a full-fledged and a more efficient multi-scale analysis involves more time and resources. In addition, it needs a coordinated team works that incorporates linguistic experts and computer science professionals. The following issues must be considered and addressed in the future work for Afaan Oromo posts multi-scale sentiment alaysis.

- ✓ The appropriate named entity recognition for the names that used for discarding the names which express the sentiment, is one of feature work to enhance the performance of the developed model in this study.
- ✓ To increase the accuracy of the sentiment classifier model we recommend the feature representation model that takes into account the position of words and that make special negation handling mechanism.
- ✓ Though explicit and regular sentiment are investigated in this work, the researcher strongly recommend the implicit and comparative sentiment analysis and approaches that combine the implicit, explicit and comparative sentences in sentiment analysis.
- ✓ If the sentiment corpus is not sufficient, the classification algorithms may not perform well in cataloging the sentiment by their polarity. Therefore, it is ideal to incorporate the Afaan Oromo standard sentiment word preparation in future work.
- ✓ It is known that the NLP tasks needs the accurate and efficient POS tagging tools for doing other computational tasks. Having this, the researcher recommend the efficient and accurate POS tagger that can handle all Afaan Oromo word categories.
- ✓ Feature or aspect level sentiment analysis concerned with identification and extraction of commented features and determining the sentiments towards these features. This paper does not reflect this, so co-reference resolution which aid the feature based sentiment analysis task and the feature based sentiment itself are another future research directions.
- ✓ Sentiment spam detection, sentiment analysis for idiomatic expressions can also be another focus of future research works.

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APPENDICES

Appendix A: Sample List of Stop-Words

-
-
(
)
dhaw
wanna
bakka
wagga
addaa
afoo
faana
eesa
eessa
eessaa
eenyu
cinaa
dura
duratti
duraa
adda
olee
ol
oli
maashaa
manee
adaa
lamaan
dur
arba
hidh
seen
hat
gad
gadi
guh
eeg
ejj
maq
baadh
fil
fuuldura
if
hed
jala
jir
jira
jiru
jidduu
dhiig
dhug
durs
duru
buh
gam
diig
aad
beek
erg
yaad
agarsiisoo
akka
akkam
akkasumas
akkaamitti
akkum
akkuma
akkanaa
ala
alatti
alla
amma
ammaa
ammaatti
ammaaf
ammaas
ammo
ammoo
an
ana
anee
ani
anaaf
attam
ati
bira
booda
booddee
dabalatees
dha
dhaan
dudduuba
dugda
dura
duuba
eega
eegana
eegasii
ennaa
erga
ergii
f
faallaa
fagaatee
fi
fullee
fuullee
gajjallaa
gama
gararraa
garas
garuu
giddu
gidduu
gubbaa
ha
hallettuu
hata`u
hatahuyyu
hamma
haga
hanga

hangahen
na
henna
hoggaa
hogguu
hoo
idda
illee
immoo
in
ini
innaa
inni
irra
irraa
irraan
isa
isaa
isaaf
isaan
isaani
isaanii
isaaniitiin
isaanirraa
isaanitti
isaatiin
isarraa
isatti
isee
iseen
ishee
isheen
isheen
ishii
ishiif
ishiin
ishiirraa
ishiitti
isii
isiin
isin
isini
isinii
isiniif
isiniin
isinirraa
isinitti
ittaanee
itti
ittiin
itumallee
ituu
ituullee
jala
jalatti
jara
jecha
jechaan
jechoota
jechuu
jechuun
kkf
kkfn
ka
kam
kan
kana
kanneen
kanamale
es
kanaa
kanaaf
kanaafi
kanaafuu
kanaan
kanaatiin
kanaatti
karaa
kee
keef
ke
kees
keenya
keenyaa
keessa
keessan
keessaan
keessatti
keeti
keetii
kiyya
ko
koo
kootu
kun
kunneen
kunniin
kunis
kuniis
lafa
lama
lachuu
maal
malee
maaliif
manna
maqaa
mataakoo
moo
na
naa
naaf
naan
naannoo
nama
narraa
natti
nu
nuti
nu`i
nuhi
nurraa
nuti
nutti
nuu
nuuf
nuun
nuy
nuyi
obbo
obboo
odoo
ofii
of
oggaa
oo
osoo

otoo	si`i	tahe	ti	walitti	yoom
otuma	sii	tahee	tiyya	warra	iyyu
otumallee	siif	tahuu	too	warri	barri
otuu	sin	ta`uu	tti	woo	ture
otuullee	siin	tahullee	unu	yaa	bara
qullii	silaa	ta`ullee	utuu	yammuu	suuta
qofa	simmoo	tana	waahee	yemmuu	ganda
sanaan	sinitti	tanaaf	waa`ee	yeroo	dhumni
saaniif	siqee	tanaafi	waa	yommii	duruu
sadii	sirraa	tanaafuu	waan	yommuu	ganama
sana	sitti	tahullee	waggaa	yoo	iyyuu
sun	sun	tahuyyu	wajjin	yookaan	duruma
sanneen	ta`e	tahuyyuu	wal	ykn	durii
sunniin	ta`u	tawullee	walirraa	yookiin	kennu
saniif	ta`an	teenya	walii	yookiini	duris
si	tahan	teessan	waliin	moo	barii

Appendix B: Sample Adjective Lists

	aatuu	ajeessaa	ariyaa	baaragaa
aagomaa	abaarsa	ajjeesaa	arjaa	badaa
aanessaa	abshaala	amanamaa	arjoomaa	badii
aangoftuu	adabamaa	angaatuu	arrabsiisaa	bajigaa
aantii	adabbii	ari`amaa	baajigaa	bakkoolaa
aaraa	ajaawaa	ari`ataa	baalbaasee	balaa

balaadhaan	bartuu	biliqqee	boosoo	ciilgee
balaafamaa	beekaa	bilisa	boroora	ciincoftuu
balaaloo	beekkataa	bilchaataa	boshoqa	cimaa
balfaa	beela`aa	bineensa	bososaa	cinqii
baqataa	beelawaa	bir`eensa	buhaa	collee
barakataa	beessee	boohaa	bu`aa	cubbamaa
baramaa	bellama	booji`aa	calaqqisaa	cubbisiisaa
bareeche	betaa	boomba`aa	caalaa	cukii
bareedaa	bibir`ataa	boonaa	caaqaa	daafaa
barfataa	biceessaa	boonsaa	cabaa	daafamaa
barfidoo	bicuu	boonsan	cabduu	daaftuu
bargoo	biddiiqaa	boora`aa	cabsiisaa	daagii
barsee	bilduu	booressaa	cerdaba	
baroo	biliqii	booroftuu	cigaa	
bayeessa	biliqiqii	booruu	cigduu	
daalee	daaqaa			
daaroftuu	dhahaa	dhugaaf	faallaa	raatuu
daba	dhara	duutuu	faal`aa	raata'aa
dafa	dheebuu	eebbifamaa	michuu	rifataa
dafaa	dheebotaa	eebba	mi`aawaa	saamaa
dannee	dhuufaa	eebbisaa	misha	urgaawaa
danqaa	dhugaa	eefa	mudaa	xiraa`aa

xurii
zeeroo
yakkamaa

Appendix C: Sample of Intensifiers

akkamalee
amanamne
aazaaba
addatti
addattiyyuu
addattuu
addumaan
addumaaniyyuu
akka-gaariitti
akka-malee
akka-maleetti
arjaa
arjoomaa
arjoomtuu
ayyaana-qabeettii
baayyee
bal`inaan
caalaa
caalaan
caalaatti
caalaattuu
canuu
cimaa
ciminaan
cimsanii
cimsee
cimsinee
cimsitee
danuu
dhugaa
dhugumaan
dhugaal
dhugaatti
dhugaattiyyuu
dhugumatti
dinqisiisaa
fayyaddaa
gad-fageenyaan
garmalee
garmaleetti
gar-tokkeen
gar-tokko
gaariitti
gartokkeedhaan
ga`aa
gahaa
guddaa
guddina
guddinaan
horaa-bulaa
guddaadhaan
gutummaaguutuutti
gutummaanguutuutti
guutummaadhumatti
guutuumaatti
guutummaatti
guutummaan
guutuutti
guutuumaatti
haalaan
haal-malee
hamma-malee
hamma-ta`een
hamma-tokko
hammam
hedduu
hedduun
heddumminaan
hedduminaan
jabinaan
jaannama
jibbisiisaa
keessaattuu
keessattiyyuu
keessattuu
keessumattuu
keessumaayyuu
maddee
maqaadhaaf
maqaaf
merqa
murteessaa
miidhaguun
miidhagaan
miidhagaatiin
mijuutti
murteessa
olitti
quxaala
qajeeltootti

qulqulleessee	ajaa`ibaa	saffisaan	ta`uyyuu	ture
sarjinaan	ajaa`iba	suuta	taanus	ulfaata
sii`oli	ajaa`ibaan	suutan	taanuyyuu	xiqqaa
sirrii	ajaa`ibuun	ta`anis	taatus	tasuma
sirriitti	sodaachisaa	ta`ullee	taatuyyuu	tasumaa
shiikkoo		ta`us	tahus	

Appendix D: List of Suffixs

ota	echa	iifuu	irraahuu	irraahillee	eenya
olee	ettii	iifis	irraahis	irrattillee	maata
olii	eechi	uma	irraan	irraanillee	maatoota
wwan	eettii	umaa	irraanuu	oota	maya
lee	eeytii	umaanuu	irraanis	n	mayoota
n	essa	umaaf	irratti	ni	a
tiin	essi	umaanis	irrattis	i	aa
dhaa	eensa	umatti	irrattuu	oolii	oo
dhaan	eensi	umattuu	illee	oolee	uu
dhaaf	eeyyii	umattis	iinillee	tti	nnoo
tii	ii	umaratti	umallee	rraa	tuu
eessa	iin	umarattis	umaafillee	ummaa	duu
eessi	iifi	itti	umaanillee	ooma	xuu
eeysa	iis	ittis		ittii	ituu
eeysi	iif	ittuu	ittillee	icha	iinsa
eecha	iinis	irraa	umattillee	ina	uumsa

oomii	atani	isa	xani	amoo	eet
een	ate	isan	xe	amta	eeti
yyii	atine	iste	xu	amtan	ees
eetii	atte	isna	oofte	amte	is
an	attu	ifte	oofti	amti	uufan
een	attan	ifna	oofna	amtuu	uufi
	atu	isise	ooftan	amuuf	uufii
na	da	isisa	oofta	ani	adhuu
ne	di	isiisa	ja	e	adhee
ni	dani	isisan	ju	eera	amani
nu	de	isiste	je	I	amanii
atini	du	isisna	jani	uu	ame
achise	duu	isista	a	uuf	amni
achisa	eenya	isistan	achuu	neerra	amu
achisan	ita	la	achiisuu	aaf	amtu
achiste	iti	lu	achuuf	aas	amtani
achisna	itani	le	adha	aat	amuu
achistan	ite	lani	adhe	aatu	omuu
aniiru	itu	ra	adhu	uuttan	oomi
anna	ina	ru	ama	uutti	oomuu
anne	inu	re	amaa	aa	oomsuu
annu	ine	xa	aman	naan	amuudhaa
ata	ise	xi	amne	u	

amuudhaa	aatii	ta	teetta	tuu	siste
f	umsa	tani	teetti	sisa	sisna
amuun	iisa	taniittu	ti	sisan	sistu
ullee	iinsa	te	tu	sise	sisne

Appendix E: Sample of Strong Positive Reviews

Hedduu gaarii dha yaada bilchaataa nama ijaaru wal jala nama deemsisu kan ifatti nu baasu. Abiyyin Uumaan Itoophiyaafi Ummatashee baay`isee haa eebbisu jechuun haasaasaanii eebbaan jalqaban. Onnee dhugaa keessatti Jaalala dhugaa baattee Warra dhiiga siif kenneef Atis dhiiga kee laatte! Kanaafuu guddina ogbarruu Oromoo reefuu lafa qabachaa jiru kana caalaatti gabbisuu dhaaf qorannoon akka kanaa taasifamuun baay'ee murteessaa dha. Ija kololaa maaloo kamba kambaa yaa qorqorroo baay'ee natti tole Taaddalaa keenyaa jabaa dhu sirboota haala yeroo waliin deemu nuuf dabali. Nyaata fayyaalessa kan akka nyaata bishaan keessaa argamaniifi muduraaleefi fuduraaleen hedduu fayyadu. Ati guddaa in gammadda dhalachuun isaas namoota baay'eetiif gammachuu in ta`a. Isaanis sagadaniifii gammachuu guddaadhaan gara yerusaalemitti deebi`an. Dhugaa jaalala akkanaa gonfachuun kennaa guddaa dha! Jawaar Mohammed essa jiraa nuf fida bishaan caalaa nu barbaachisa. Dhugaa rabbii juneyidiin bayyee nama jabaa dha yeroo bulchiinsa isaa keessati nama baayyee hojate dha. Nuyi durboonni sitti in gammadna in ililchinas Jaalala kees daadhii waynii caalaa in jajanna durboonni hundinuu dhuguma si jaallatu. Dhugaa keeti yaa dr Abiiyi ati duru hayyuu dha jennee sii jaalanne! Waaqqayyo Siihaa eebbisu Dooktara Abiyu Ahmed dhugaa jettaan. Ergamichi isheetti mul`atee Waaqayyo gooftaan sii wajjin jira`o nagaan siif haa ta`u yaa ayyaana-qabeettii ittiin jedhe. Ati dubartoota hundumaa caalaa eebbifamtuu dha mucaan garaa ke keessa jiruus eebbifamaa dha. Barnooni meeshaa dhalli namaa dinagdeenhawaasummaan fi siyaasaan ittiin jijjiramu keessaa isa guddaa dha. Dhaamsi gugguddaa har`a Yunivarsiitii AMboo mooraa guddaatti darbe bareedaa dha. Namni amantiidhaan fuula Waaqayyoo duratti qajeelaa ta`e jireenya dhugaa in jiraata. Nutis baayyee baayyee galatoomaa Rabbi umurii dheeraa isiniif haa kennu jechuu barbaadna. Baayyee bareeda hamtuuun isiin hin argini gaariin isiin hindarbiiin

Appendix F: Sample of Positive Reviews

Waaqayyo ifichi gaarii akka ta`ee in arge. Waxabajjii guyyaa jaalalaa fi tokkummaa ummatoota Itoophiyaa. Ummanni Oromoo garuu ummata kamiiyyu akka ofiitti ilaala ni hammata ni jaalata.

Waliin guddachuu wal kabaja fi wal jaalalaan jiraachuu ummata duudhaa godhatee dha. Kanaaf yaa uummata kiyya jabaa dhaa abdiin qaba fuuldurri keenya ifaa dha jedhan. Ambaasaaddarittiin gama isaanitiin dirreen siyaasaa biyyattii nagayaan akka bal`atu tasgabbiin hojjetamaa jiraachuu himaniru. Guyyaan harraa gammachuu kiyya daadaa keenya akka sidheebonneeru idoo beektee. Jeneraal Tsa`areen akka amala nama dhunfaatti nama bayyeessa nama hundumaa wajjiin walii galu turan jedhu Jeneraal Haayluu Gonfaa. Ummaatni keenya ummaata nagaa jaalala beekuu kabaja qabu dha. Walaloonke akka dammaa mi`oofti haqa jirus dubbateeta galatoomi! Kaayyoon keenyaa lammiin oromoo tokkollee akka hin hidhamne hin reebamne hin gidirfamne dha. Hiriyyoota waliin hariiroo hawaasummaa gaarii qabaachuun fayyaa gaarii qabaachuuf ni gargaara. Itoophiyaan nageenya waaranaaf xiyyeeffannaa kan kennitu ta`uu fi mariin siyaasaas haala gaarii irra jiraachun isaan gammachiisuu eeran. Inni kun ilma koo isa jaallatamaa dha gammachuun koos isaatti in raawwatama. Akkuma sagaleen nagaa kee gurra koo keessa bu`een mucichi gammachuu dhaan garaa koo keessa burraaqe. Abdiin gooftaan kenne akka raawwatamu beektee kan amante attam kan ayyaanomtee dha. Kan du`e galuu baatu adabbiin kun haqa qabeessaa fi qajeelummaan kennamuun gaarii dha. Nama kabajuun mallattoo sodaa ykn loogummaa osoo hin taane bilchina sammuufi dandeettii fageessanii yaaduuti.

Appendix G: Sample of Strong Negative Reviews

Akka ragaan qorannoo mul`isutti moobayiliin suuta osoo nuti hin beekiin karaa baay`ee dhan miidhaawwan guddaa fi hanga du`atiin kana nugeesisuu danda`u nutti fiduu dandaa`u dha. Obbo Baqqalaa Garbaa irratti dhageeffachaa ture dhimma Lixaa oromiyaa hedduu gaddee rakkoon Uummatnii keenya keessa jiru nutti agarsiise bara dhufuuf sodaachisaa tahu cimsee dubbatee qotee bulaan qonnaa irraa hin jiru jedhee barattootnii barnoota irra hin jiran jedhee. Hedduu dhuguun baay`ee balaa qaba. Nami haadha manaa isaa gad dhiisuun humnaan ishee irratti kahu baay`isee nan jibba. Ergamaan Waaqayyoo dingata isaan dura dhaabatee ifni surraa gooftichaas naannoo isaanitti ibse kana irratti isaan na`anii guddaa sodaatan. Abbaan kee anis baay`ee yaaddofne si barbaadaa turre jetteen. Mana sagadaa keessa kan turan hundinuu kana dubbachuu isaa yommuu dhaga`an baay`ee isaatti aaran.Yakkamaan Obbo Katamaa Raggaasaa jedhamu guyyaa har`aa dhaddacha manni muttii olaanaa Godina Shawaa Bahaa har`a oolen ragoota hedduu booda hidhaa cimaa umrii guutun adabameera.Jireenyi Ummata Keenyaa kun Ani Baayyee na gaddisiisa. Haala ati keessa jirtu hedduu gaddisiisaa akka ta`e beeka. Har`a akkuman Facebook baneen Dargaggoo Abdii Lammeessaa du`aan addunyaa kanarraa boqote jechuu dhaga`ee hedduun gadde.Waliin nyaataa dhugaa tti maqaa nama dhahuun daba guddaa dha. Oromoo hedduminaan ajjeesaa fi hiisisaa oromoo fakkachuuf yaaluun hin danda`amu. Dogoggora abbootii keenyaarra deebi`uun salphina guddaa dha! Rakkoon keenya inni guddaa rakkoo siyaasaa biyya kenyaati jedhan hanga rakkoon siyaasaa hinsirrannetti duulli biqiltuu dr aby ofaa jiru kun duuluma mallasaan abbayyaa jedhe ummata gowwoomsaa ture ta`a. Callisuun kee Hedduu nu miidhaa jira!Silaa ilmi namaa waan jedhu hin dhabu namoonni tokko tokko waa otuu adda hin baafanne diinaaf dubachaa oolu yeroo waa arginu utaalleetuma shaneedha yoo janne sirrii miti uummanni oromoo shanees ta`e paartilee biraa odp irraan kan hafe abdii irraa hin qaban.

Appendix H: Sample of Negative Reviews

Itti fayyadama moobayiliitiin wal-qabatee rakkoon fayyaa fi du`an nama gahu jira. Jiraattonni magaalaa Asallaa tajaajila daandii fi ibsaa argachuu hin dandeenye jechuun komatan. Sii irrraa hin ilalamuu ati silaa yoom akka namaa sammun yaadda koomee keetiin yaadaa siif kan yaada sif kennu gowwaa dha. Yaa dhama`aa of wallalaa! Yoo qajellumni si jirate Rabbi si qajelchu Beekan Gulumma ykn ammo hin olchiin hin bulchin Rabbi dandetti ofitin waan hojii keeti sitti haa agarsisu. Yaa Boni Intala Oromoo Yohanis namumaa miti. Hiriiricha Irrattis shiftaan Hidhatee Ummata Keenya gidirsaa Jiru Qabsoo Keenya Bakka hin Bu`u. Xannee boo`i! Abiyyiin harreen kun kan gaafa abbaan isaa du`uu xis-ximbis hin jennee gaafa habashaan wal fixxe taa`ee boo`e. Kanaan uummata jibbisiifna jedhanii yaaduu gowwummaa dha. Sareen badduun saree gara ofii nyaatti jedhani! Namittiin hattuun kun bara kan akka wayyaaneen Aangoo dhuunfattu godhe isheedhaa ammammoo maal munaagdi akka waan nutti ishee hin beennetti. Munaagduun kun! Abiyyii anaaf diina kan Wallaggaa Gujii Boorana Shawaa fixaa jiruu eenyu. Hogganaan Mana Maree Baalaadaraa Calalaqaan Jaal Iskindiree Naggaa Keenyaas tibbana rakkina hidhamuu kittilayyoolee isaatif mootummaa komatee jira. Abiyyiin Alagaa dura dhaabbatee nu salphise xiiqeesse diina nuuraati goobsee Oromo nurratti dhaane. Har`a immoo Jawarin dabalatee naannoo keenya irraa gara Hawaasaatti kan imalan hundi saamichaaf malee hojii gaariif miti jedhee olola jibbiinsa hamaa nurratti oofaa jira

APPROVAL SHEET

HARAMAYA UNIVERSITY

POST GRADUATE PROGRAM DIRECTORATE

MACHINE LEARNING BASED MULTI-SCALE SENTIMENT ANALYSIS FOR AFAAN OROMO POSTS

Submitted by:

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