ADDIS ABABA UNIVERSITY
SCHOOL OF GRADUATE STUDIES
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DEPARTMENT OF COMPUTER SCIENCE

OPINION MINING FROM AMHARIC BLOG

BY
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Dedicated to:

1. **My Mother Mulunesh Alemu**

   Mom: *You have passed through many challenges in order to change my life. Mom hope you remember all the obstacles that could not made you give up.*

2. **My Father Tilahun Hailu**

   Dad: *This is the way towards what you want me to be. I am here because of your inspiration and motivation during my childhood up to this work and continue. Dad you did not stop serving me though challenges resists you at different time.*

3. **My Brother Habtamu Tilahun**

   Habtish: *Your question was always when will I marry, and my answer was after the graduation. You are not lucky to see your wish, may your soul rest in heaven!*

4. **My Darling Samirawit Tsegaye**

   Honey: *Unforgettable advice "Don't Fear For Facing Failure In The First Attempt Because Even Successful Maths Also Starts With Zero Only and above all You belong to Jesus" I wish I could call you everything for me! My mother, my sister, my wife… you have helped me in my entire career starting from being of my special loved.*

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Acronyms and Abbreviations

OM	Opinion Mining
IR	Information Retrieval
POS	Part of Speech
NER	Named Entity Recognizer
NLP	Natural Language Processing
DB	Data Base
VS	Visual Studio
C#	See Sharp

Abstract

Before the Web, organizations have been conducting a survey and people have been asking their family, friends and neighbors for the information (factual or opinion) in order to make a wise decision. With the growing popularity of sophisticated and advanced technologies like the Web, the world has become a single village. It is possible to get documents expressing opinions that are generated, propagated, exchanged, stored and accessed through the Internet. The accumulation of vast and unstructured opinions on the web has been making information acquisition difficult. Opinion mining is the preliminary technique towards tackling this obstacle. It can be performed in one of the three different levels: sentence, document or feature level. Among the three levels, feature level opinion mining is the detail and complex but has a better advantage to meet customers and organizations need.

Although there are many feature level opinion mining models that have been developed for foreign languages, as far as the researcher‟s knowledge is concerned, there is no feature level opinion mining scheme for Amharic language. Therefore, this study proposes feature level opinion mining model for Amharic language by employing manually crafted rules and lexicon. The proposed model consists of five major components that can extract features, determine opinion words regarding identified features with their semantic orientation, aggregate multiple opinions and generate structured summary.

Two experiments have been conducted for features extraction and opinion words determination by using 484 reviews from three different domains. The first experiment indicated that an average precision of 95.2% and recall of 26.1% were achieved in the features extraction and an average precision of 78.1% and recall of 66.8% were achieved in the determination of opinion words. The precision of the second experiment in features extraction gets lower by 15.4% whereas the precision of opinion words determination gets higher by 1.9% and the recall of both features extraction and opinion words determination gets higher by 7.8% and 25.9% respectively when compared to the first experiment. Thus, our experimental results demonstrate the effectiveness of the techniques we have applied.

Keywords: Opinion, Opinion Mining, Review, Blog, Semantic Orientation, Sentence Level, Document Level, Feature Level, Classification, Extraction, Determination.

Chapter One - Introduction

1.1 Background

With the growing of web technologies such as blogs, forums and various other types of social media, it becomes possible for people to find useful information in a factual or/and opinion forms. An opinion is a person's ideas and thoughts towards something. According to Merriam-Webster"s Online Dictionary [21], the term opinion is a view, judgement, or appraisal formed in the mind about a particular matter. Hence, an opinion is not a fact because it can"t be proven. If it becomes proven or verified later, it is no longer an opinion, but a fact. Accordingly, most information on the web from a surfer's perspective is better described as an opinion rather than a fact [2]. Gradually opinion on the web becomes vast and unstructured by its nature to get relevant information that can be used in decision making process. A technique called opinion mining has been proposed as a remedy of this issue.

Opinion Mining (OM) is a recent discipline at the crossroads of information retrieval (IR), text mining and computational linguistics which tries to detect the opinions expressed in the natural language texts [2]. Opinion mining, which is also called sentiment analysis, involves building a system to collect and examine opinions about the product made in blog posts or comments or reviews. It can be useful in several ways. It helps users to judge the success of an advertisement campaign or a new product launch, determine which versions of a product or service are popular and even identify which demographics like or dislike particular features. For example, **a review might be broadly positive about a digital camera, but be specifically negative about how heavy it is**. Being able to identify this kind of information in a systematic way gives the vendors a much clearer picture of public opinions than surveys or focus groups, because what praises or criticisms are from wide range of their customers via website.

The ideal opinion mining tool would process a set of search results for a given item, generating a list of product attributes (quality, features, etc.) and aggregating opinions about each of them (poor, mixed, good) [22]. Much of the research, self-identified as opinion mining, fits this description in its emphasis on extracting and analysing judgments on various aspects of given items. However, the term has recently also been interpreted more broadly to include many different types of analysis of evaluative text [12].

The field of OM is recent; as a result there are a lot of challenges to be met. According to [12], current techniques are still primitive for opinion identification and extraction. Both sentiments and subjectivities are quite context sensitive and quite domain dependent. The same expression may impose different polarity for different domain. For example, a "**large**" mobile phone gives negative meaning to that phone model, whereas a TV with "**large**" screen gives positive meaning to users of TV screen. On the other hand, a word may indicate different opinions in the same domain. For instance, "**The battery's life is long**" the word "long" indicates positive opinion where as "long" in "**It takes a long time to focus**" indicates negative opinion.

One may think that it is simple to classify and summarize opinions by using simple keywords. The three machine learning methods (Naive Bayes, maximum entropy classification, and support vector machines) put to use by [13] do not perform as well on sentiment classification as on traditional topic based categorization. According to them, sentiment classification is a very challenging research area.

People can express their opinions in different ways; some give general information while others provide detail. And also some bounce from one product feature to another with only a brief description while others elaborate on certain features. These factors have a particular importance during classification of the text orientation, positive or negative. Two or more sentences may refer to the same or different features. Similarly, depending on the user interest one sentence can express many opinions within it. Accordingly, there are three levels of opinion mining: sentence level, document level, and feature level opinion mining.

Sentence level opinion mining polarity determination is at the sentence level towards the target object. There are two main tasks in sentence level opinion mining. The first is subjectivity classification which classifies the given sentence either as subjective or objective and the second is sentiment determination which determines the polarity of subjective sentence if it is positive or negative or neutral. For instant, **"ይህ ጥሩ አምባር ነው / This is a beautiful bracelet**". This sentence is classified as subjective, and its sentiment is determined as positive.

Document level sentiment classification is concerned with classifying the document based on the overall opinion expressed by the user or customer. All the user‟s review sentences are considered. For instant, **“ቆንጆ ካሜራ ናት:: ነገር ግን ፎቶዎቿ ጥራት ዬላቸውም:: /It is a beautiful camera. However, its images’ quality is poor**”. The first sentence is positive while the second one is negative whereas the resultant polarity is neutral.

Feature level opinion mining first discovers the detailed targets on which opinions have been expressed in a sentence, and then determines whether the opinions are positive, negative or neutral. The targets are objects, and their components, attributes and parts. An object can be a product, service, individual, organization, event, topic, etc. For instance, in a product review sentence, it identifies product features that have been commented on by the reviewer and determines whether the comments are positive or negative. For example, **ጥሩ አገልግሎት ያለዉ ሆቴል ነዉ /The hotel has good service.** The target in this sentence is **አገልግሎት** (Service) of the **ሆቴል** (Hotel) object and the opinion is positive, **ጥሩ** (Good). Many real life applications require detailed analysis in order to make product improvements. One needs to know what components and/or features of the product are liked and disliked by consumers or users. Such information is not discovered by both document and sentence level sentiment classification.

1.2 Statement of the Problem

A website is a collection of related web pages containing images, videos or other digital assets [15]. There are a number of Web-based services and applications that have been built using the building blocks of the technologies and open standards that support the Internet and the Web. Web-log or blog is one of the many applications of the web. It refers to a simple webpage consisting of brief paragraphs of opinions, facts, personal diary entries, or links called posts, arranged chronologically with the most recent first [14]. According to [14], most blogs also allow visitors to add a comment below a blog entry. There are many, free and priceless, web software that are used to create blog and other tools like visual studio, MySQL and languages like C# with ASP scripting language. The blog can be part of companies‟ website for the collection and display of users‟ idea about the services or products.

Before the web, when an individual needs to make a decision, he/she typically asks for opinions from friends and/or families and when an organization needs to find opinions of the general public about its products and services, it conducts surveys and/or organizes focused groups. With the fast growing development of the Web, the number of documents expressing opinions becomes more and more important [3]. One can post reviews of products or post comments at merchant sites and expresses views on the Internet forums, discussion groups, and blogs. Now if one wants to buy a product, it is no longer necessary to ask one‟s friends and families because there are plentiful of product reviews on the Web which give the opinions of the existing users of the product. For a company, it may no longer need to conduct surveys to organize focused groups or to employ external consultants in order to find consumer opinions or sentiments about its products and those of its competitors.

The number of opinions on the web is increasing from time to time. As a result, finding opinion sources and monitoring them on the Web can be a difficult task. And also, in many cases, opinions are hidden in long forum posts and blogs. It is very difficult for a human reader to find relevant information, extract important sentences, read them, summarize them and organize them into usable forms or to decide some thing using such unstructured information. So, there is a need for an automated opinion mining and summarization system for these reviews. For these reasons many researches on sentiment analysis have been done and are being undertaken for English and other languages such as Chinese, Thai, etc [7, 35, 38].

The amount of Amharic documents on the web is increasing [4]. Nevertheless, as far as researcher‟s knowledge is concerned feature level opinion mining system for Amharic language was not developed. Despite the fact that a document level sentiment classification of Amharic documents was studied [1], it fails to show parts that are liked or disliked by the customer. A positive document on an object does not mean that the customer has positive opinions on all aspects or features of the object. Likewise, a negative document does not mean that the customer dislikes everything about the object. In an evaluative document, a product review or service comment, the customer typically writes both positive and negative aspects of the object although the general sentiment on the object may be positive or negative. To achieve such detailed aspects, feature level opinion mining is needed.

1.3 Objective of the Study

1.3.1 General Objective

The general objective of this research work is to develop feature level opinion mining and summarization model for Amharic language.

1.3.2 Specific Objectives

To realize the aforementioned general objective, the study aims to carryout the following specific objectives:

a. Extensive study of available literatures on the opinion mining approaches and techniques.
b. Analysis on the general grammatical structure of Amharic sentences with the aim of identifying and extracting features and determining sentiment.
c. Study the lexical category of Amharic language to identify constructive properties to feature level opinion mining.
d. Construct lexicon of Amharic opinion words.
e. Create blog and text database.
f. Collect reviews for the performance evaluation.
g. Design architecture, algorithms and rules for the identification and extraction of objects" features and opinions related to identified features from Amharic reviews in order to realize the proposed model.
h. Develop a prototype to demonstrate the validity of our model.
i. Evaluate the model.

1.4 Methodology

The following methods will be employed to achieve the above stated objectives.

1.4.1 Literatures review

Opinion mining related literatures from different sources such as published papers, journal, articles and other materials will be reviewed in detail to get better understanding of the area and to have detail knowledge on the various techniques of opinion mining.

1.4.2 Data Processing

Hotel, university and hospital domain reviews will be collected manually for this research work. And the following pre-processing activities will be performed by developing and adopting existing tools in addition to manual processing:

- Data cleaning which involves removal of objective sentences, non opinion sentences, from the given reviews. Even though opinion holders (people who provide opinion) are expected to write their opinion regarding one or more features of the target object, they are always free to write whatever they feel. Their reviews may not be genuine reviews rather facts or questions which cause confusion for the opinion mining procedure and resulting in unreliable output. For instance, **ይህ ቸኮላታ ጣፋጭ ነው ወይስ መራራ? / Is this chocolate sweet or bitter?** This is a sentence that seeks answer and not considered as a review. We will remove such sentences at the early steps of the process. Furthermore, we will try to correct spelling errors by realising the intention of opinion holders. For instance, **ሀቴል** corrected to **ሆቴል**, **ቀርስ** corrected to **ቁርስ, etc.**
- We will collect reviews from different individuals by using the forms of appendices A, B and C. Since we aimed to deal with the reviews that are posted on the blog, we will develop a blog at appendix D and all manual reviews from different opinion holders will be posted on this blog. These reviews should come together for further analysis. We will achieve this through data integration. Multiple reviews from different sources will be stored into a coherent text database that we will be designed for this purpose.
- Normalizing different letters of Amharic script that have the same sound, homophone characters, while integrating the reviews, for instance we will change **ኸ** and **ሐ** to **ሀ**.

Moreover, pre-processed Amharic reviews will be stored into text database and then exported to .txt file format with encoding UTF-8 which is appropriate file format for the Python programming language for further analysis.

1.4.3 Analysis of Opinion Based Amharic Texts

Since this research work will be concerned with opinionated Amharic texts, it is compulsory to analyze the nature of Amharic text that contains opinions. Consequently, rules and methods will be proposed to identify and categorize opinions on the features of the objects. We will consult a linguistic professional for better understanding on the relationship between features and opinions in Amharic text.

1.4.4 Create Lexicon of Amharic Opinion Words

We will create lexicon of Amharic opinion words by considering three target domains (hotel, university, and hospital). Also some of opinion terms that were created by Selama [1] will be incorporated into our lexicon. Each word in this lexicon will be labelled by either positive (+) or negative (-) sign according to their basic polarity. For instance, **ጥሩ/good** is labelled with **"+"** while **መጥፎ/bad** is labelled with **"-"**.

1.4.5 Design Approach

To model feature level opinion mining from Amharic blog, rule based approach will be taken into consideration. The rule based approach relies on handcrafted rules.

1.4.6 Selecting Tools for Implementation

The main tools that will be used in conducting this research work are: HornMorpho 2.2 software, for morphology analysis; Notepad, for text operation; MS-Word, for document writing; MS-Excel, for performance analysis; MySQL, for creating text database; Visual Studio 2008, C#, ASP, for creating blog; and Python 3.1, for implementing the algorithms.

1.4.7 Conducting Experiment

Feature level opinion mining involves identification and extraction of features and determination of the sentiments along these features and generate summary in a tabular form. Nouns will be considered as features and adjacent adjectives will be determined as opinion words in this work. The effectiveness of features extraction and opinion words determination will be measured using precision, recall and F-measure.

1.5 Beneficiaries

The outcome of this research work will be helpful in the following areas:

1.5.1 Product/Service Benchmarking and Market Intelligence

The key to selling a product and quality services is responding to customers" demands at proper time and at the right location. Many companies spend large amount of money on market analysis and hire specialized consulting companies. The proposed feature level opinion mining model can aid this effort and potentially minimize costs and increase productivity of the companies.

1.5.2 Individual Needs

The outcome of this work can be potentially used by any Internet users. The model is designed to generate structured reviews which can be easily used by the individual for decision making.

1.5.3 Placing Advertisement in User-generated Content

The model can be used as an advertisement means when one praises a product using it.

1.6 Scope and Limitations

1.6.1 Scope

Feature level opinion mining model for Amharic language requires a number of natural language processing tools such as sentence parser, chunker, part of speech (POS) tagger, stemmer, and so on. Even though some of the NLP tools have been done by some researchers, they are not publicly available to use them in our model. Having these limitations in mind, the scope of this study will be:

- Consider Amharic syntax regarding adjectives and nouns.
- Develop Amharic opinion words for service domain.
- Design summary in a tabular form which consists of five fields such as features/አስተያየት የተሰጠበት ሁኔታ, total number of opinions/ጠቅላላ አስተያየት, positive/አዎንታ, negative/አሉታ and unclassified/ያልተለዩ).

1.6.2 Limitations

Due to this and time constraint, the following are out of the scope of this research work:

- Semantic and context based features extraction and opinions determination.
- Determining adjective that far from the noun.
- Generating Amharic opinion words automatically.
- Extraction and summarization from Amharic expressions such as "ቅኔያዊ አነጋገር".
- Detecting and eliminating false or misinforming comments.
- Checking the legitimacy of the opinion holder.

1.7 Organization of the Thesis

The whole thesis is organized into Six Chapters including the current one. The Second and the Third Chapters are about literatures review and related works respectively. The Fourth Chapter deals with the design and implementation of our model. The Fifth Chapter focuses on the experimental and performance analysis of opinion mining system. The last Chapter is about drawing conclusion that comprises both summary of the work done and future works.

Chapter Two - Literatures Review

2.1 Opinion Mining

Extraction of relevant information from vast text is a good idea in natural language processing. Extraction of factual information is part of information retrieval (IR) while extraction of opinion is part of opinion mining (OM).

People have found subjective sentences very important in making genuine decision. Today millions of web-users express their opinions about many topics through blogs, wikis, chats, and social networks. The interest that individual users show in online opinions about products and services, and the potential influence such opinions have is something that vendors of these items are paying more and more attention. The number of subjective sentences is increasing on the web. This has been opening a door for Opinion Mining (OM) that has been used to extract and summarize opinion for faster decision making. It is concerned with the identification of opinions in a text and their classification as positive, negative or neutral. Opinion identification is more difficult than the topic based one and it cannot be based on just observing the presence of a single word.

This chapter mainly deals with the basic components, levels and common approaches of opinion mining.

2.2 Basic Components of Opinion Mining

Basic components of opinion mining are: opinion holder, opinion and object [2]. An opinion holder is either a person or organization that holds a specific opinion on a particular object where as an opinion is a view, attitude, or appraisal on an object from an opinion holder and an object is an entity which can be a product, a person, an event, an organization, a topic, or even an opinion that is criticized or appraised by opinion holder. Basically there are two ways to express opinions: direct opinions and comparison [12]. Direct opinions usually describe one object and contain some adjectives that refer to it. For example, **the image quality of my mobile phone is good**. This sentence consists of an object “mobile phone” and an adjective “good” which modifies the image quality of mobile phone. The comparative statements mention more than one item and describe some sort of relation. Example: **the image quality of my mobile phone is much better than Abebe's mobile phone**. On the other hand the superlative statements mention more than two items and describe relation of an item with the remaining items. For example, **the image quality of Kebede's phone is best when compared to ours.**

2.3 Levels of Opinion Mining

The main task in opinion mining is determining semantic orientation of a text at different levels. The three levels that were introduced under Section 1.1 are described in detail in the following sections.

2.3.1 Sentence Level opinion mining

Subjectivity identification is the first task in sentence level opinion mining [39]. They have investigated the idea of creating a subjectivity classifier that uses lists of subjective words learned by two bootstrapping algorithms: Meta-Bootstrapping and Basilik algorithms that were designed to learn words that belong to a semantic category. According to the authors both algorithms need seed words and unannotated text corpus as input. They have mentioned a relevant annotation scheme that was developed for a U.S government sponsored project with a team of 10 researchers in 2002 for the identification and characterization of subjective words in a sentence. According to them, sentences are labelled by two classifiers: first for subjective sentences and second for objective sentences. The sentences that are not clearly classified into any category are left unlabelled and omitted at this stage. Both of the classifiers are based on preset list of words that indicate sentence subjectivity. The subjective classifier looks for the presence of words from the list, while the objective classifier tries to locate sentences without those words. According to the results presented by the researchers, their classifiers achieved around 77% recall with 81% precision during the tests.

Hatzivassiloglou and Wiebe [45] also studied subjectivity identification at sentence level by considering the impact of adjectives. Semantically oriented adjectives and gradable adjectives were used for subjectivity classification and prediction. Their work was largely exploratory regarding interaction of different characteristics of adjectives in the prediction of subjective sentences. Incorporating their investigation to machine learning models for the prediction of subjectivity was part of their plan.

Another work on sentence level is work of Kim and Hovy [46]. They have presented a system that automatically determines sentiment words within a sentence and combining them by having a pre defined topic. Their system works in four steps: First it selects sentences that contain both the topic phrase and holder candidates. Next, the holder-based regions of opinion are delimited. Then the sentence opinion classifier calculates the polarity of all opinion bearing words individually. Finally, the system combines them to produce the holder‟s sentiment for the whole sentence. They experimented with various models of classifying and combining sentiment at word and sentence levels with promising results.

Additional work on sentence level sentiment analysis was the work of Michael Gamon et al [48]. They have developed a prototype system called Pulse which has been used to extract taxonomy of major categories (makes) and minor categories (models) of cars in order to process according to two dimensions of information: sentiment and topic detection from large quantities of car reviews text database. According to them, first the sentences for a make and model of car have been assigned to clusters and have received a sentiment score from the sentiment classifier then visualization component displays the clusters and the keyword labels that were produced for the sentences associated with that car. Their classifier considered three classes: positive, negative and "others". The researchers stated that the technique they have described was simple but effective for clustering sentences and a bootstrapping approach have been applied for sentiment classification. Their experiment indicates that they achieved some of the best results on the negative and "other" classes. Automatic spelling correction is the future work in addition to identification of sentiment vocabulary and sentiment orientation with minimal customization cost for a new domain.

The last work on sentence level opinion mining is the work of Barbosa and Feng [43]. The researchers have proposed the use of meta-information about the words on tweets and characteristics of how tweets are written in order to classify sentence of the tweets as subjective or objective, and in order to determine the subjective tweets as positive or negative. Their approach uses biased and noisy labels as input to build the models. According to them their solution is more effective and robust while more detailed analysis of sentences is a future work.

2.3.2 Document Level Opinion Mining

Document level sentiment classification is concerned with classifying the document based on the overall opinions that have been expressed by the opinion holder as positive, negative or neutral.

Selama [1] has studied document level sentiment mining for opinionated Amharic text using general and domain specific opinion terms. His model has components such as: pre-processing, sentiment word detection, weight manipulation, polarity classification and polarity strength. According to the researcher, all positive sentiment terms are tagged in the lexica by „+" and given a default value of +2 at run time while all the negative sentiment terms are tagged by „-" and given a default value of -2. Before the final average polarity weight is calculated, the polarity propagation is done which is used to modify the initial value of the sentiment terms. This modification of the initial value or weight is done only if the sentiment word is linked to a modifier term (negations or intensifiers). Accordingly the polarity of the review is determined by the resultant sum of polarity value of opinion terms in the reviews. If the resultant sum is greater than zero then the review is categorized as positive. Similarly, if the resultant sum is less than zero then the review is categorized as negative. Also if the resultant sum is equal to zero then the review is taken as neutral. According to him, tests on the prototype were done using movie and newspaper reviews where the obtained result with these test data is encouraging.

Another work on document level sentiment analysis is the work in [13] which considered overall sentiment for the classification of a document. The aim of their work was to examine whether it suffices to treat sentiment classification simply as a special case of topic-based categorization with two topics, positive and negative, or whether special sentiment categorization methods need to be developed. They experimented with three standard algorithms: Naïve Bayes, Maximum Entropy, and Support Vector Machines classifications. Having movie reviews as data, they found that standard machine learning techniques definitively out perform human-produced baselines. However, from their experimental result they realized that sentiment categorization using machine learning techniques is more difficult than topic based classification. Work in [24] on the classification of reviews was the closest to their work.

Work in [24] is also a document level sentiment analysis which presented a simple unsupervised learning algorithm for classifying reviews as recommended (thumbs up) or not recommended (thumbs down). The researcher considered an average semantic orientation of the phrases in the review that contain adjectives or adverbs in order to classify a review. According to the researcher, the semantic orientation of a phrase is calculated as the mutual information between phrase and the word excellent minus the mutual information between phrase and the word poor. Accordingly, semantic orientation of the review is recommended if the average semantic orientation of its phrases is positive. The author collected around 410 reviews in four different domains from Epinions for the evaluation and found the proposed algorithm achieved an average accuracy of 74%. According to the researcher, two main limitations were observed: required longer time for query processing which can be improved by computer with higher processor, and level of accuracy for movie domain becomes down which can be improved by the combination of proposed algorithm with a supervised classification algorithm.

Work in [44] also studied document level sentiment analysis. They have developed a methodology for extracting small investor sentiment from stock message boards. They have applied statistical and natural language processing techniques to extract opinion from the boards. According to them, messages are classified into one of the three types: bullish, bearish and neutral by using five classifiers: Naïve classifier, Vector distance classifier, Discriminant-based classifier, Adjective-Adverb phrase classifier, and Bayesian classifier. The researchers mentioned that some of these classifiers are language dependent while others are independent. From their performance evaluation, their idea was worth pursuing.

2.3.3 Feature Level Opinion Mining

Sentiment classification at both document and sentence levels is general; whereas feature level sentiment analysis is the most detailed study. Being most useful it is also the hardest and the most complex to perform. It identifies the key pieces of information that should be mined and describes how a structured opinion summary can be produced from unstructured texts. In feature level sentiment analysis, at least the following major tasks need to be performed [9, 10]:

- Extract object features that are commented
- Identify opinions used towards these features
- Determine orientation of opinions (positive/negative/neutral)
- Group feature synonyms and produce a summary.

Many feature level opinion mining models were proposed for different languages. Some of them are discussed in Chapter 3.

2.4 Common Approaches to Opinion Mining

Many opinion mining researches have been done by employing different approaches. Depending on how rules are acquired, the most common approaches to opinion mining are: rule-based, statistical, and hybrid approaches. In subsequent sections each approach is detailed.

2.4.1 Rule-based Approach

Rule-based approach is the method that is intrinsic to natural languages. It is based on common Natural Language Processing (NLP) methods such as part of speech tagging, co-reference resolution, syntactic and semantic analysis of a text and parsing made by a functional and relational analyser [41]. Rule based approach has been used to analyse the text sentence by sentence and extracts the relationships that convey feelings by utilizing linguistic knowledge on sentiment words and opinion related heuristic rules as clues for opinion analysis [10, 36, 37].

Turney‟s work [24] is one of the earliest influential papers that used part of speech tagging to estimate a semantic orientation of meaningful phrases in Epinions reviews. Also work in [28] follow the same logic, used part of speech tagging, as the work of Turney [24] with the difference that they used WordNet to define the semantic distance between the adjectives of a text and a set of already tagged words. According to the researchers, the distance is defined as the path length between two graph nodes. They calculated the distance of a word from both "good" and its antonym "bad" and they proposed three measures: the evaluative measure ("good"/"bad"), the potency measure ("strong"/"weak") and the activity measure ("active"/"passive").

In rule based approach the researchers have the possibility to develop a grammar for a specific application and to add new rules to extract the relationships which they are interested in. Therefore, the researchers can change the extraction-rules (e.g., add rules for a new relationship), increase/decrease the number of words in the lexicon that act on the rules, remove certain parts of the processing, etc. There are also possibilities of the development of sentiment lexicon and annotation of the text under rule based approach.

In the development of sentiment lexicon, the analysis of the text is based on the words in the lexicon that have received specific features marking the positive or negative feelings. Most of the words are verbs and adjectives but also some common nouns and adverbs. The size of the lexicon varies depending on the domain of application. The quality of lexicon-based sentiment classification systems depend on the effectiveness of the sentiment lexicon. Hu and Liu [10] proposed a lexicon-based method to use opinion bearing words in the opinion mining task. They dealt with product reviews from Websites in order to produce a summary with positive and negative statements made for product features. They identified features such as camera size, image, etc. by selecting the frequent words, assuming that people often use the same words to describe features. Then they identified opinion sentences and their orientation. According to them, an opinion sentence is a sentence that contains both feature and at least one adjective. They have used a seed list of 30 basic adjectives. For each adjective in the reviews, they checked whether it is in the seed list or it is an antonym or synonym of a word in the seed list. Every time the orientation of an adjective is found, the seed list is expanded with this adjective. The infrequent features are identified by looking for the nearest noun phrases to an opinion word. Finally, each sentence is given the orientation of the majority of its part-orientations.

Another work that is based on lexicon of sentiment words is the work of Ding and Liu [29] which improved the previously mentioned work in [10] by using linguistic rules. According to them, a positive word was assigned the semantic orientation score of 1, and a negative word was assigned the semantic orientation score of -1. The researchers have considered the distance between feature and the opinion word. Accordingly, a low score is given to the opinion words that are far from the feature. The work in [7] is very similar with their work.

A holistic lexicon based approach for opinion mining was proposed in [7]. According to them, their approach succeeded in the extraction of context based opinion words which were major difficulties for the previous researchers. They also dealt with how to extract special words, phrases, and a way to combine multiple conflicting opinion words in the sentences. The experimental result from the system they have implemented showed that their approach outperforms existing methods significantly.

2.4.2 Statistical Approach

In the statistical approach, rules are not written manually as rule based approach; rather they are acquired from large size corpora. The statistical method is based on machine learning technique which uses unsupervised, or/and supervised learning to construct a model from a large training corpus. Machine learning based approaches have been used to train the machine learning based classifiers using sentiment features such as sentiment words, word bi-grams, word n-grams, syntactic patterns, punctuations, topic relevant features, etc. Therefore, statistical approach begins with a model and estimates parameters of the model based on data.

Some researches have employed a supervised training approach in opinion mining [22, 25]. They start with collecting training dataset from certain Websites. According to them, an ideal training sample should be representative in order to get good accuracy of prediction. Also the researchers have indicated that not properly categorized data should be labelled manually by humans. The next step is to train a classifier on the corpus. Once a supervised classification technique is selected, an important decision to make is feature selection. In text classification, features denote properties of textual data which are measured to classify the text, such as word position, header information, and ordered word list. After appropriate features have been selected, the classifier is trained on the training dataset. The training process is usually an iterative process in order to produce a better model. The performance of the classifier trained on the training data is finally evaluated on the test dataset based on chosen criteria.

Work in [13] also examined several supervised machine learning methods for sentiment classification of movie reviews and concluded that machine learning techniques outperform the method that is based on human-tagged features although none of the existing methods could handle the sentiment classification with a reasonable accuracy.

Another work which is based on supervised machine learning is the work of Esuli and Sebastian [30]. They have presented a method by assuming the terms with similar orientation tend to have similar glosses. They have investigated on the top of SentiWordNet, work of [23]; a lexical resource where each dataset is associated to a score describing how positive, negative or objective the particular dataset is. The score is the proportion of a group of classifiers that are used in order to label every dataset.

Kanayama and Nasukawa [8] proposed a method with the intention of solving the problem of using simple opinion bearing words by expanding lexicon of opinion words automatically. According to them, the lexical entries to be acquired are called polar atoms. They used the overall density and precision of context coherency for successively same polarities in the corpus and the statistical estimation picks up appropriate polar atoms among candidates without any manual tuning of the threshold values. Their experimental results show that the precision of polarity assignment with the automatically acquired lexicon was 94% on average, and confirmed that their method is robust for corpora in diverse domains and for the size of the initial lexicon.

2.4.3 Hybrid Approach

Both rule-based and statistical approaches have their own pros and cons (Table 2.1). Thus, rule-based and statistical approaches are usually combined to benefit from their synergy effect that rises to hybrid approach. Even supervised and unsupervised learning techniques that were mentioned under rule based and statistical approach have their own pros and cons. For instance, according to [33], supervised machine learning is likely to provide more accurate classification result than unsupervised semantic orientation but a supervised machine learning model is tuned to the training corpus, and thus needs retraining if it is to be applied elsewhere.

According to [27], machine learning is subject to over-training and highly dependent upon the quality of training corpus. In addition, with machine learning algorithm, it could be difficult to incorporate contextual valence shifters [11].

Nowadays opinion mining is designed by considering more approaches; one approach is not full fledged by itself to achieve the best accuracy. Thus hybrid approach combines sentiment knowledge, machine learning and a general linguistic framework for opinion analysis. For instance, the work of Kim and Hovy [40] incorporated both rule based and statistical approaches. They have presented a method that could identify opinion holders and opinion topics. In order to achieve their goal, they have performed two tasks: first, they have colleted opinion words and related frames by using FrameNet data. Then, they applied statistical approach for labelling semantic roles in a sentence. Their experimental result shows that their system performs significantly better than the baseline.

Table 2.1: Rule-based Versus Statistical

Rule-based Approach	**Statistical Approach**
Requires linguistic expertise	Not much linguistic expertise required
Training dataset is not required	Large and ideal training dataset required
No frequency information	Based on frequency information
More brittle and slower	Robust and quick
Often more precise	Generalized model built from corpora
Error analysis is usually easier	Error analysis is often difficult

2.5 Amharic Language

Ethiopia is a country with diverse languages in which Amharic is the most commonly spoken and designated working language of the Federal Republic of Ethiopia. The Amharic language belongs to the Semitic language family. It uses a special writing system called the Ge‟ez or Ethiopic alphabet.

One of the most cited classical works on Amharic grammar, written in Amharic, classifies the word classes of this language as eight, Mersehazen [32]. These are preposition, noun, conjunction, interjection, verb, adjective, pronoun, and adverb. Recent work by Baye Yimam [31] has stated that Amharic has only five word classes. He did by leaving out interjection from the inventory and putting together prepositions and conjunctions in one class and considering pronouns as a subclass of nouns. Baye‟s reduction of Mersehazen‟s classification seems to be based on the role of words in syntax, i.e., considering words that have clear role in Amharic sentence grammar.

Amharic is a challenging language for a number of reasons. It has a very complex morphology as compared to English language. This is due to the unique nature of the Amharic language. Amharic language is highly inflectional and derivational that makes morphological analysis very complex. Also, many times, writers misspell the words by accident; especially reviewers whose Amharic is not their mother tongue use third (ሣልስ) and sixth (ሳድስ) phonemes interchangeably.

In Amharic language, there are also many characters that are pronounced the same but symbolically different, homophones. This increases the number of features going to be extracted without any advantages. For example: **ሀ**ይለኛ and **ሐ**ይለኛ, there is no clear rule to use **ሀ** or **ሐ,** people use such characters for semantically same words interchangeably.

In Amharic language, there are many ways of writing words especially loan words, words that are taken from other languages. For example, the word computer can be written as **ኮምፒዩተር** or **ኮምፒውተር**.

2.5.1 Lexical Category of Amharic Language

Part of speech or lexical category of Amharic language explains how the Amharic words are used in the Amharic sentence. Morphologically important parts of speech for this thesis work are nouns and adjectives.

A noun is the name of a person, place, thing, or idea. According to Getahun Amare [5], Amharic nouns are of two types: basic and derived nouns. Basic nouns are nouns that stand with their own to give meaning. For example: **ቤት፣ መሬት፣ እሳት፣ ወንበር፣** etc. Derived nouns are nouns that are derived from verbal roots, adjectives, stems, compound words and nouns. Amharic nouns can be marked for:

- **Number (ቁጥር)** by affixation of morphemes or repetition of words. For instance, the noun, "ወንበሮች" is obtained from the combination of morphemes "ወንበር" and "-ኦች" whereas the noun "ጌጣጌጥ" is obtained from the repetition of the word "ጌጥ".

- **Definiteness (እምርነት)** by affixation of morphemes based on number and gender. Either ኡ or ዉ is affixed for male definite noun and ዋ or ኢቱ or ይቱ is affixed for female definite noun. For instance, the noun "ፈረሱ" is obtained from the morphemes "ፈረስ" and "-ኡ" whereas the noun "ዶሮዉ" is obtained from the morphemes "ዶሮ" and "-ዉ".
- **Gender (ፆታ)** by affixation of the morpheme ኡ or -ኢት. Example, the noun "ልጅቱ" is obtained from the morphemes such as "ልጅ", "-ኢት" and "-ኡ".
- **Objective (ተሳቢ)** and **possessive (ዘርፍ)** cases by affixation of the morphemes -ን and -ኤ respectively based on person, number and gender. The word "ልጁን" is an objective noun which is obtained from the morphemes "ልጅ", "-ኡ" and "-ን" whereas the word "ልጄ" is a possessive for the first singular noun which is obtained from the morphemes "ልጅ" and "-ኤ"

Adjectives are words which describe or tell us of the qualities of the nouns by being before them. But it is not always true that a word before a noun is an adjective. It is not also true that adjectives always come before nouns. Example: **ምግባቸዉ ጥሩ ነዉ::** ጥሩ is an adjective which comes after the noun ምግባቸዉ. Adjectives are also of two types similar to nouns, basic adjectives such as: **የዋህ፣ ደግ፣ ሞኝ፣ በጎ፣** etc. Derived adjectives are derived from verbal roots, nouns, stems, and compound words. Amharic adjectives can be marked for number, definiteness, gender and objective case by affixation in a similar way to nouns.

- **Number (ቁጥር)** by affixation of morphemes or repetition of words. For instance, the adjective, "ጅሎች" is obtained from the combination of morphemes "ጅል" and "-ኦች" whereas the adjective "ረዣዥም" is obtained from the repetition of the morpheme "ረዥ-ኣ-ዥም".
- **Definiteness (እምርነት)** by affixation of morphemes based on number and gender. ኡ for male definite adjectives and ዋ or ኢቱ is affixed for female definite adjectives. For instance, the adjective "ትልቁ" is obtained from the morphemes "ትልቅ" and "-ኡ".
- **Gender (ፆታ)** by affixation of the morpheme -ኢት along with the morpheme -ኡ. Example, the adjective "ትልቂቱ" is obtained from the morphemes such as "ትልቅ", "-ኢት" and "-ኡ".
- **Objective (ተሳቢ)** case by affixation of the morpheme -ን on the adjectives. The adjective "አሮጌውን" is an objective adjective which is obtained from the morphemes "አሮጌ", "-ዉኡ" and "-ን".

Chapter Three - Related Works

Many feature level opinion mining researches have been conducted. Though, most of them are for English language there are also some feature level sentiment analyses for other languages. This chapter briefly discusses some of the feature level opinion mining researches for both English and non-English languages.

3.1 Feature Level Opinion Mining for English Language

The idea of sentiment analysis at different level was discussed by Liu [42]. The researcher elaborated main points of feature level opinion mining. According to the researcher, feature level opinion analysis first discovers the targets on which opinions have been expressed in a sentence, and then determines whether the opinions are positive, negative, or neutral. The targets are: objects, components, attributes and characteristics. An object can be a product, service, individual, organization, event, topic, etc. For instance, in a product review sentence, it identifies product features that have been commented on by the reviewer and determines whether the comments are positive or negative. For example, in the sentence, "**The battery life of this camera is too short**", the comment is on "battery life" of the camera object and the opinion is negative. The researchers noted that many real life applications require this level of detailed analysis in order to make product improvements. One needs to know what components and/or features of the product are liked and disliked by consumers.

Feature level opinion mining has an advantage than that of both sentence and document level sentiment analyses. But, it is more complex and difficult when compared to the others due to the nature of problems in feature level opinion mining. Three variables have been used in [7] in order to understand problems in feature level opinion analysis for English language:

D - Set of reviews

F - Set of features

W – Set of opinion words towards F.

According to them, three problems were clearly identified and stated as follows:

Problem 1: Both F and W are unknown. Then, in opinion analysis, researchers need to perform three tasks:

Task 1: Identifying and extracting object features that have been commented on in each review $d \in D$.

Task 2: Determining whether the opinions on the features are positive, negative or neutral.

Task 3: Grouping synonyms of features, as different people may use different words to express the same feature.

Problem 2: F is known but W is unknown. This is similar to Problem 1, but slightly easier. All the three tasks for Problem 1 still need to be performed, but Task 3 becomes the problem of matching discovered features with the set of given features F.

Problem 3: W is known (then F is also known). The researchers only need to perform Task 2 above, namely, determining whether the opinions on the known features are positive, negative or neutral after all the sentences that contain them are extracted.

Clearly, the first problem is the most difficult to solve. Problem 2 is slightly easier. Problem 3 is the easiest, but still realistic.

The authors dealt with the third problem. They could determine semantic orientations of opinions towards product features by searching, mining and summarizing these opinions. According to the researchers, most existing techniques utilize a list of opinion bearing words which imposes major shortcoming. They have proposed a holistic lexicon based approach for the determination of semantic orientation that overcomes shortcomings of existing methods. They could also aggregate multiple opinion words in a sentence. According to them, previous researchers have considered only explicit opinions expressed by adjectives and adverbs. In their work, both explicit and implicit opinions have been considered. Their method also handles implicit features represented by feature indicators. These made their technique more complete and their experimental results showed that the proposed technique performs markedly better than the existing methods.

Another feature level opinion mining for English text is the work of Hu and Liu [10]. Their work can be considered as the pioneer work on feature-level opinion summarization. For feature level opinion summarization they used their previous work [19]. The work in [19] could extract features and opinion words toward these features. Their feature extraction algorithm is based on heuristics that depend on feature terms‟ respective occurrence counts. Their method does not need corpus to perform tasks. They used association rule mining based on the Apriori algorithm to extract frequent item sets as explicit product features (only in the form of noun phrases). Two measures have been developed to evaluate association rules, which are support and confidence. According to them, item sets that have support at least equal to minimum support are called frequent item sets. In their work, each resulting frequent item set is a possible feature. They defined an item set as frequent if it appears in more than 1% minimum support of the review sentences. In this approach, the algorithm does not consider the position of the words in a sentence. In order to remove incorrect frequent features, they used feature pruning that consists of compactness pruning and redundancy pruning. To evaluate the proposed methods, the researchers conducted the experiment by using the customer reviews of five electronics products: 2 digital cameras, 1 DVD player, 1 mp3 player, and 1 cellular phone. The reviews were collected from Amazon.com and C|net.com. For each product, they first crawled and downloaded the first 100 reviews. These review documents were then cleaned to remove HTML tags. After that, NLProcessor [47] is used to generate part of-speech tags. Their system which was designed for this purpose is then applied to perform summarization. The system has a good accuracy in predicting sentence orientations and the average accuracy for the five products is 84%. Accordingly, their method of using WordNet to predict adjective semantic orientations and orientations of opinion sentences are highly effective.

The work in [19] was improved by the work in [18] by proposing a technique based on language pattern mining to identify product features from pros and cons in reviews in the form of short sentences. The researches have proposed this method to compare features of different objects. According to the researchers, this is the first work that helps to choose features of different objects by looking at the difference. They also made an effort to extract implicit features. They extracted features from the reviews that are written positive and negative opinions separately which is easier for the extraction when compared to extracting features from the reviews in free format. They implemented a prototype system called Opinion Observer. According to the researchers, using this system the user can realize the strengths and weaknesses of each product clearly in the minds of consumers in terms of various product features. Experimental evaluation indicates, regarding synonym grouping, 52% recall and 100% precision as the method is very conservative. The main problem with their simple method is that it did not handle context-dependent synonyms.

The work in [16] extended the work in [19] by extracting features for capturing knowledge from product reviews. In their method, the output of [19] was used as the input to their system, and the input was mapped to the user-defined taxonomy features hierarchy thereby eliminating redundancy and providing conceptual organization. Hu et al [19] used shallow parsing and association rule for features extraction. Also they have identified the expressions of opinions associated with features; they used adjacent adjectives as opinion words that are associated with features. According to them, after identifying the frequent features the system extracted nearby adjective as an opinion.

Another feature level opinion mining that has been developed for English text was the work of Somprasertsri and Lalitrojwong [20]. They have proposed an approach for mining product features and opinion words based on syntactic and semantic information. Their goal was to develop ways that can establish a correct relationship between the product feature (the topic of the sentiment) and the opinion word (the subjective expression of the product feature). The basic purpose of their approach is to mine the product features and opinion words that are associated with product features in each sentence. The researchers parsed the review sentences by using the Stanford Parser. After that they exhaustively generated a dependency and identified a noun phrase as a product feature candidate. For each product feature candidate in every dependency parse tree, they searched for the related opinion words. Some adjectives and verbs may be used for both favourable and unfavourable opinions. The researchers used Maximum Entropy model to predict the opinion-relevant product feature relation and classifying product feature-opinion pair using syntactic information. It is quite natural that customers will often refer to identical product features using inconsistent or incompatible terminology. Furthermore, customers might refer to a particular feature in different ways. For example, "**memory card", "compact flash", "compactflash", "CF card", and "memory stick"** are strings for describing "removable memory". To solve this issue, they used semantic information encoded in ontology. The researchers have constructed product ontology manually by integrating manufacturer product descriptions and terminologies in customer reviews. The root of the tree represents the product. Subsequent sub-trees represent attributes of the product. They conducted 5-fold cross validation on the dataset and employed the OpenNLP Maximum Entropy package as their classification tool. To evaluate the method, the researchers used precision, recall, and F-score to measure the effectiveness of their approach. When dealing with multiple datasets (i.e., 1250 sentences), they adopted the macro average to assess the overall performance across all datasets. The macro average is calculated by simply taking the average performance obtained for each dataset. Accordingly, they have conducted experiments and compared the results with the results of the work of in [10]. The result of their experiments showed that their approach is more flexible and effective. Polarity determination and production of structured sentence list were not included in their work.

The work of Popescu and Etzioni [9] is also feature level. They have developed an unsupervised information extraction system called OPINE, which could extract product features and opinions from reviews. OPINE first extracts noun phrases from reviews and retains those with frequency greater than an experimentally set threshold and then assesses those by OPINE"s feature assessor for extracting explicit features. The assessor evaluates a noun phrase by computing a Point-wise Mutual Information score between the phrase and feature discriminators associated with the product class. They applied manual extraction rules in order to find the opinion words. This idea is similar to that of [19], but instead of using adjacent adjectives, they defined extraction rules to find the expressions of opinions.

Another earlier work on the feature level opinion mining on top of English text is the work of Yi and Niblack [50]. They have developed a set of feature term extraction heuristics and selection algorithms for extracting a feature term from product reviews. According to the researchers feature term is a part of relationship with the given topic, an attribute of relationship with the given topic, and an attribute of relationship with a known feature of the given topic. In the first step, they extracted a noun phrase with the Beginning define Base Noun Phrase (bBNP) heuristics. Then, they have selected a feature term from the noun phrase.

The last feature level opinion mining for English language is work in [49]. They have proposed a multi-knowledge based approach for movie review mining and summarization. They have used WordNet and labelled training data to generate a keyword list for finding features and opinions. Grammatical rules between feature words and opinion words were applied to identify the valid feature-opinion pairs. Summary in list form was obtained as an output. Their experimental results showed that the proposed approach was effective.

3.2 Feature Level Opinion Mining for Chinese Language

Works in [38] and [34] were some of feature level opinion mining for Chinese language.

Supervised method was used for product features extraction and unsupervised method to group the product features in [38]. The authors mainly focused on the first step; extracting product features in Chinese customer reviews while others remain as their future work. Morphemes and opinion words were proved to be the important components to capture the semantic similarity among product features in the process of product features categorization. The experimental results show that their method was effective and promising.

Supervised approach was employed for features extraction and unsupervised for grouping of features and opinion words and also identifying hidden relationship between them in [34].

3.3 Feature Level Opinion Mining for Thai Language

Work in [35] proposed feature level opinion mining method for the Thai language. Their approach was based on the syntactic pattern analysis of two lexicon types. The first is three domain dependent lexicons such as features, sub-features and polar words. The second is six domain independent lexicons such as particles, negative words, degree words, auxiliary verbs, prepositions and stop words. Having these lexicons, they have constructed a set of syntactic rules based on the frequently occurred patterns. According to them, their method was effective in most cases.

3.4 Summary

Though our work is similar with the related works as all of them extract opinions at feature level, there are many differences between our work and the related works due to the nature of the languages. In Amharic, most of the time a word that changes polarity comes after a noun or after an adjective whereas in English it comes before a noun or before an adjective. For example, **“not** good**”** would be written as “**ጥሩ አይደለም”** in Amharic. Also lexicon of Amharic opinion words is totally different from any other languages‟ lexicon.

The tasks that we have engaged with are similar with the tasks of problem 1 that were elaborated under section 3.1. In our work F is not known before processing the review text and W is determined by using predefined lexicon of opinion words.

Chapter Four - Design and Implementation of Feature Level Opinion Mining from Amharic Blog

4.1 Design

Identifying and extracting features, determining opinions regarding identified features, organizing and summarizing unstructured subjective text are the most common activities in feature level opinion mining.

Some characteristics of the Amharic language are taken into consideration for the intended feature level opinion mining. Among these characteristics, the first one is devising a means of identifying and extracting nouns as features by analyzing the basic nature of Amharic nouns and the second one is, designing the way of determining adjectives that modify the nouns as opinions by investigating major nature of Amharic adjective words. Moreover, the way of summarizing reviews depending on the features and opinions along these features will be elaborated in this Chapter. We have adopted the work of Michael Gasser [26] for the first characteristic and we have created the lexicon for the second characteristic.

Apart from the language characteristics there was a simple user friendly interface or blog by which a user feeds his/her reviews to a database and an interface through which results will be displayed in a tabular form so that the users easily get information they need. We have designed this blog and reviews database to meet the goal of this study.

4.1.1 Approaches and Techniques

The process of feature level opinion mining from Amharic blog takes a review as input via a blog, extracts the features, determines the opinions, and produces a summary as an output, see Figure 4.1.

In the field of opinion mining, the problem of identifying and extracting features and opinions and then generating the summary can be tackled using different approaches. Some of the notable ones are rule-based, statistical, and hybrid approaches.

From the definitions of the aforementioned approaches and techniques, it is possible to infer that rule based approach has an implication on the design and development of the feature level opinion mining system for Amharic language. Therefore, the design and development of this thesis work is based on the rule-based approach.

4.1.2 Architecture of Feature Level Opinion Mining from Amharic Blog

The general architecture of feature level opinion mining from Amharic blog is given in Figure 4.1. The architecture has five major components, these are:

- Text Operator,
- Morphological Analyzer,
- Feature Extractor,
- Opinion Extractor, and
- Feature-Opinion Summarization.

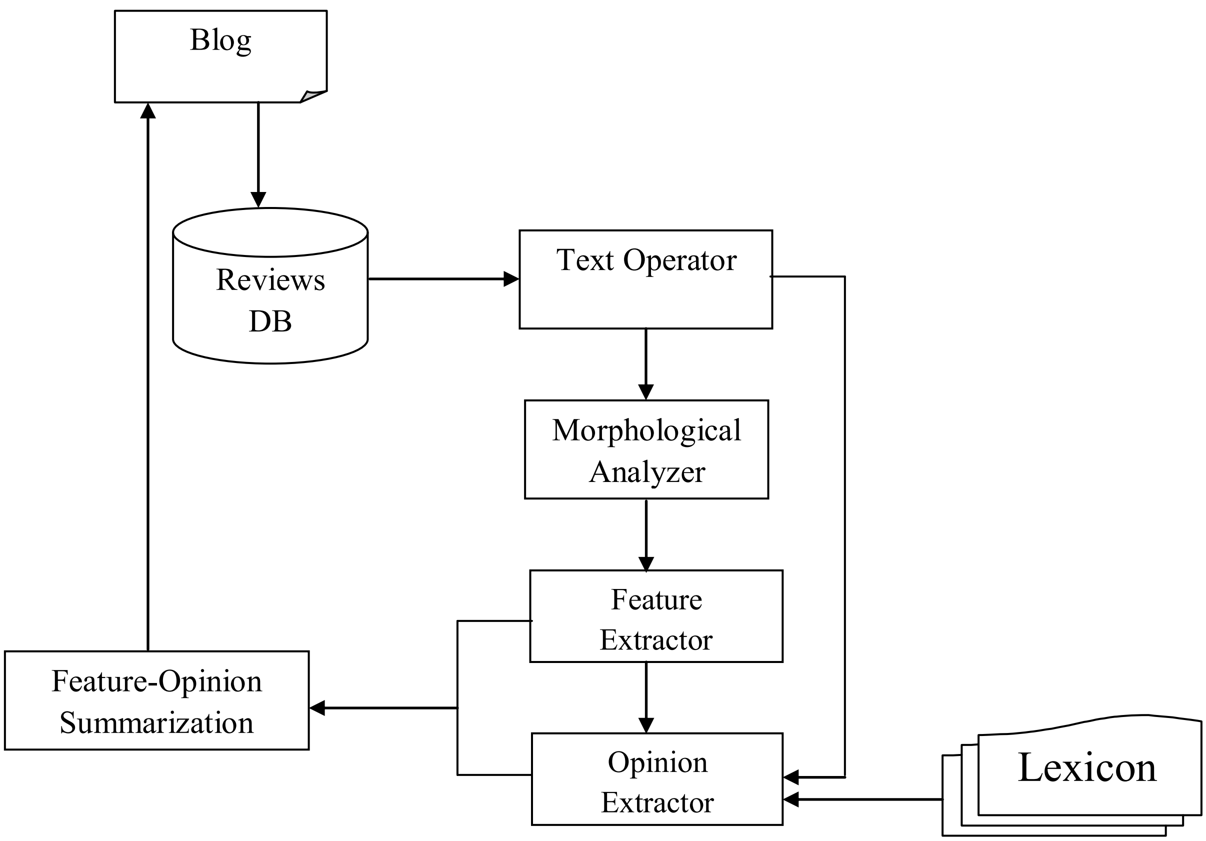

Figure 4.1: General Architecture of Feature Level Opinion Mining from Amharic Blog

4.1.2.1 Text Operator

Since the morphological analyzer component accepts data only in text format, reviews in the database were exported to a file in a text format. Texts read and write operations have been performed on the text editor for further analysis.

4.1.2.2 Morphological Analyzer

We have used Michael Gasser‟s HornMorpho 2.2 to analyze the reviews. HornMorpho is a Python program that analyzes Amharic, Orominya, and Tigrinya words into their constituent morphemes (meaningful parts) and generates words along with their class category based on their morphology. Figure 4.2 shows the architecture of the morphological analyzer.

Figure 4.2: Architecture of Morphological Analyzer

4.1.2.3 Feature Extractor

Feature extractor component takes analyzed text from the morphological analyzer component and extracts the nouns as features.

4.1.2.4 Opinion Extractor

The objective of Opinion Extractor component is to determine opinion words toward features that were extracted through Feature Extractor component. Figure 4.3 shows the process of opinion words determination along with their polarity.

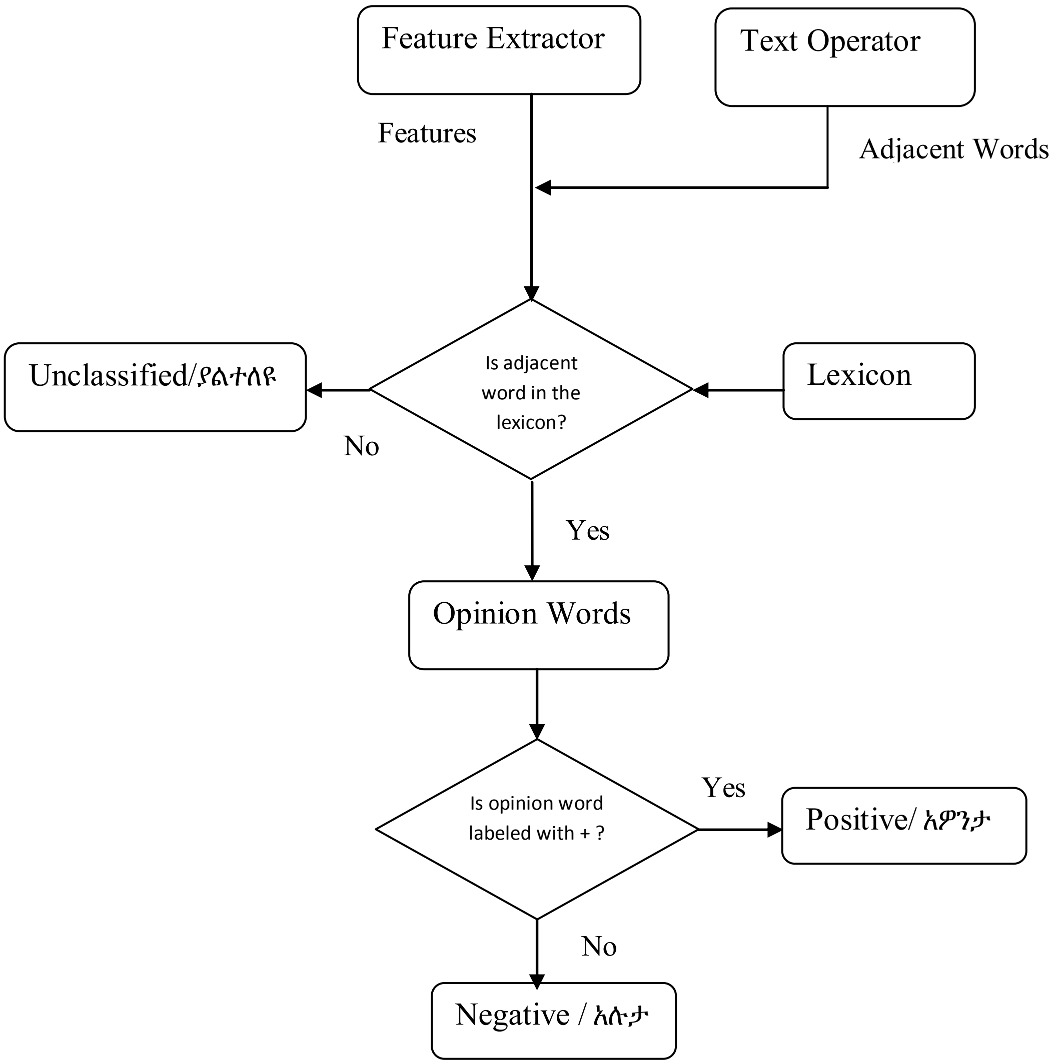

Figure 4.3: Flow of Processes in Opinion Words Determination

4.1.2.5 Feature-Opinion Summarization

This component takes the output of feature extractor and opinion extractor components and group frequent features along with their opinons. Here, frequent features are features that occurred two or more than two times by having adjective that exists in the lexicon at the left or right side. The threshold two was determined expermentally while analyizing performance.

4.2 Implementation

4.2.1 Tools

The tools that we have used for prototype development are: Microsoft Visual Studio 2008, MYSQL DB, Text Editor, Hornmorpho 2.2 and Python. The rationale behind the choice of Python programming language is since it is an easy to learn but powerful programming language especially for text processing in NLP applications [6]. It has elegant syntax and dynamic typing, together with its interpreted nature makes it an ideal language for scripting and rapid application development in many areas, particularly in natural language processing on most platforms.

In the following sections, the details starting from the user interface for the data entry to the implementation of the Feature-Opinion summarization are presented.

4.2.2 User Interface/Blog

A blog is a discussion or information site consisting of discrete entries or posts typically displayed in reverse chronological order by being part of companies‟ website. Blog can be used as a good place of online brand advertising of a particular individual or company. Also users can post or view opinions via the blog regarding something. We have developed the blog using VS 2008 environment, C# language and ASP in order to help users send reviews via it, see Figure 4.4, and customers can view some body‟s reviews as a whole, appendix D, and also the summary as well, see Figure 4.7.

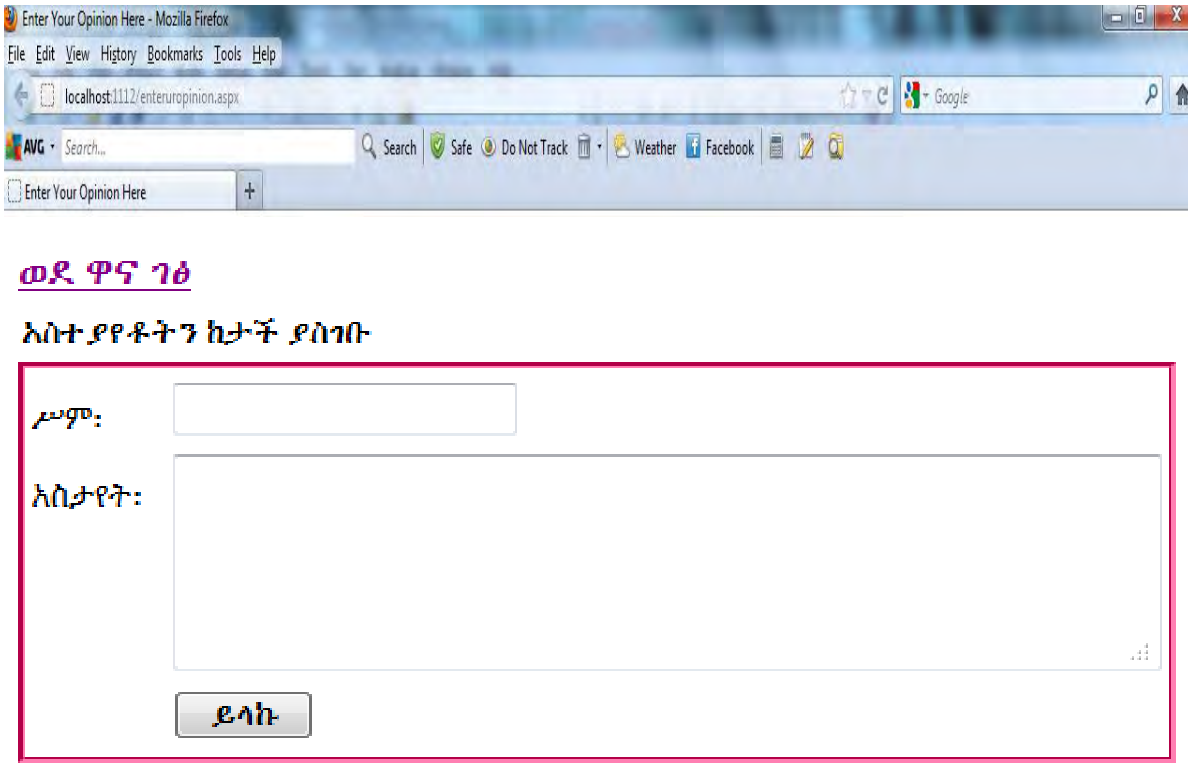

Figure 4.4: Opinion Entry Blog

4.2.3 Review Database

We have used MYSQL database for the development of text database in which users‟ reviews are stored. Reviews that have been collected from three different domains were stored into the hotel, university and hospital tables of this database. The blog of Figure 4.4 was used to send reviews to the database for further processing.

4.2.4 Features and Opinion words Identification and Extraction

By having our early definition of the word feature and further analysis on the collected reviews, we could realize that most features candidates are nouns. Also, we could observe from the collected reviews that almost all opinion words are adjectives.

Examples:

1. **ጥሩ ምግብ ይሰራሉ::** **ጥሩ** is an opinion while **ምግብ** is a feature
2. **ባለጌ አስተናጋጅ ነዉ::** **ባለጌ** is an opinion while **አስተናጋጅ** is a feature

These conventions led us to deal with the main problems, a way of identifying and extracting features and opinions from unstructured Amharic text, which need to be solved. For the identification and extraction of features and opinions from unstructured Amharic text, we need Amharic POS tagger. Unfortunately, though research on Amharic POS has been done, it is not publicly available to use. However, we succeeded to find a software called HornMorpho which tags a noun and an adjective as a noun. We have consulted the author why did he tag the adjective and the noun under the same class category and his response was due to their morphological similarity. According to the author, HornMorpho is not a real POS tagger rather it is a morphological analyzer. Hence, noun and adjective have been tagged as a noun. Though noun and adjective are morphologically similar, they are different in their parts of speech and as such they should be tagged accordingly. In order to overcome this issue, we have carried out the following activities:

First, reviews have been collected manually. Then, these reviews were stored into the text database via the blog. The reviews in the database were exported to a text file which is compatible file format to feed it to HornMorpho. Then, the output from HornMorpho was also kept in text file format. This is the file from which we have extracted candidate features. We could identify and extract features from this text by using their category name labelled as a noun. The following two rules have been used in order to identify nouns from adjectives:

Rule 1: First identify a word labeled as a noun and then looking for a modifier of this noun at either left or right hand side by using lexicon. If there is a modifier around this noun, this noun can be taken as a potential feature.

Rule 2: If rule one is fulfilled and this noun is frequent with threshold two, then the noun will be extracted as a real feature and will be kept on the text editor.

The reason for checking the existence of a modifier around a noun is to ignore nouns lacking modifier to be a candidate features; most probably these nouns are used to convey a fact and not commented by opinion holders. For instance, **ብልጦ ምግብ ማብሰያ ዕቃ ገዝታለች።** In this sentence, there is no modifier around the noun "**ብልጦ**" that is derived from an adjective word **"ብልጥ"** and in the same way the noun "**ምግብ**" lacks a nearby modifier. So, these two nouns will be ignored by the sytem. Infact these nouns may be modified by a modifier which is far from the nouns but this is a very rare occurance. Actually, failing to determine these modifiers may put a minor impact on the performance of our system.

The importance of considering only frequent nouns is to identify real nouns from adjectives; some adjectives that have a nearby modifier are going to be taken as a feature. If we fail to ignore them by using Rule 2 above, these adjectives will be displayed to the users as being features which degrade performance, precision, of the system. By analyzing the whole reviews we could observe the adjectives that have modifiers are almost not frequent; often they don‟t occur more than one time. So, such adjectives could be ignored to be extracted as being features. But the adjectives that fulfill both rules will be extracted and listed in the summary according to their polarity in the same way to the features. On the other hand, we missed some features that have a nearby adjective and occurs only one time throughout the reviews due to Rule 2. Hence, recall of the system in extracting features is expected to be down. Figure 4.5 shows the algorithm that identifies and extracts features.

```
BEGIN
  Store reviews into the database
  Export Reviews in the database to text file 1
  Feed text file 1 to HornMorpho and save output as text file 2
  While not end of file 2
    DO
      Iteratively identify words labeled as noun and save as text file 3.
      Check nouns in file 3 that have nearby modifier and occur more
      than two times in file 1 then kept these nouns on the buffer.
    END
END
```

Figure 4.5: Algorithm for Features Identification and Extraction

4.2.5 Polarity Determination and Summarization of Feature-opinions

We have developed a lexicon of Amharic opinion words. These words are general opinion words for service domains. Employed lexicon, consists of 578 (appendix H) negative and 423 positive (appendix I) opinion words. Among 1001 opinion words more than half are from Selama‟s [1] work and the remaining are ours. We have used this lexicon to check whether the words around the features are opinion words or not and also to determine the polarity of words around the features.

Opinion holders write their ideas by using opinion words, features and words that can change previous polarity. From collected reviews, we realized that opinion holders have used these words by putting them in different places in the sentences. We elaborate the idea by declaring three variables as the following:

- F to represent feature
- O to represent opinion word and
- CP to represent word that changes previous polarity of the opinion word

Opinion holders mostly use one or two of the following patterns while writing their opinions regarding some thing.

Let "i" be a counter in which i=0 indicates a place where the first feature is located. Then the possible places of O and CP are:

Pattern 1: Reviews with O at i-1 and no CP. Example, **አሪፍ ምግብ ነው፡፡** The word at i=0 is F which is **ምግብ** while the word at i-1 is O which is **አሪፍ**.

Pattern 2: Reviews with O at i-1 and CP at i+1. Example, **አሪፍ ምግብ አይደለም፡፡** The word at i=0 is F which is **ምግብ** while the word at i-1 is O which is **አሪፍ** and the word at i+1 is CP which is **አይደለም**.

Pattern 3: Reviews with O at i+1 and no CP. Example, **ምግቡ ጥሩ ነው፡፡** The word at i=0 is F which is **ምግቡ** while the word at i+1 is O which is **ጥሩ**.

Pattern 4: Reviews with O at i+1 and with CP at i+2. Example, **ምግቡ አሪፍ አይደለም፡፡** The word at i=0 is F which is **ምግቡ** while the word at i+1 is O which is **አሪፍ** and the word at i+2 is CP which is **አይደለም**.

Patterns 1 and 2 are written according to the linguistic general rule; adjective is a word that comes before a noun to modify it. On the otherhand, adjectives of Amharic language can come after the definite Amharic nouns. Accordingly, Patterns 3 and 4 are created. Polarity changer word comes after a noun as in Pattern 2 and after an adjective as in Pattern 4. If adjacent words exist in the lexicon, these words will be determined as opinion words and then looking for their semantic orientation. Positivity or negativity of a word implies the polarity of opinion holder on that feature. Incorporating all possible opinion words in the lexicon has a positive effect on the performance of the system. In real world, this is difficult but not impossible. Figure 4.6 shows how to determine polarity of opinion words and how to summarize multiple opinions along features. Figure 4.7 shows the sample output of our prototype.

R represents reviews from opinion holders

F represents features in R

O represents opinion word

i=0 represents initial place of F

n represents maximum number of multiple O on the same F

counter=1 represents counting number of n opinions along same F.

j=1 represents initial number of first F in R and increased to hold different F.

pc=0 represents initial value for positive opinion word

nc=0 represents initial value for negative opinion word

```
BEGIN
while not end of R
DO
  while counter of Fj <=n and Fj at i
   DO
        If  word at i-1 exist in the lexicon
            If word at i-1 assigned with "+"
                pc ← pc+1
            else
                nc←nc+1
        elseif word at i+1 in the lexicon
            if word at i+1 assigned with "+"
                pc←pc+1
            else
                nc←nc+1
        if word at i+2 in the lexicon
            if word at i+2 assigned with "-"
                if word at i+1 assigned with "+"
                    pc←pc-1
                    nc←nc+1
                else
                    pc←pc+1
                    nc←nc-1
        if word at i+1 in the lexicon
            if word at i+1 assigned with "-"
                if word at i-1 in the lexicon
                    if word at i-1 assigned with "+"
                        pc←pc-1
                        nc←nc+1
                    else
                        pc←pc+1
                        nc←nc-1
                else
                    pc←pc
                    nc←nc
            uc←n-(pc+nc)
       counter←counter+1
   END
 j←j+1
END
END
```

Figure 4.6: Algorithm for the Opinions Extraction, Polarity Determination and Summarization.

አስተያየት የተሰጠበት Feature	ጠቅላላ አስተያየቶች	አዎንታ	አሉታ	ያልተለዩ
አገልግሎት	37	28	5	4
መኝታ	10	5	1	4
ጋርደን	2	2	0	0
ምግብ	48	34	4	10
ሰረተኞች	3	2	1	0
ሆቴል	19	12	5	2
ሬስቶራንት	24	17	4	3
ቁርስ	2	2	0	0

Figure 4.7: Sample Feature-Opinion Summary

Chapter Five - Experiments and Performance Analysis

5.1 Introduction

Every system is developed to meet some functionalities. These functionalities are evaluated to make sure that the systems are performing effectively. Effectiveness refers to the extent a system fulfills its objective. In the case of our prototype system, the exactness of extracting relevant features and the exactness of determining polarity of opinion words are evaluated. Testing environment, manual data collection, evaluation metrics such as: precision, recall and F-measure, expermental results and discussions are all sub topics that will be discussed in the subsequent sections.

5.2 Testing Environment

The testing has been done on a laptop computer with Windows 7 ultimate operating system, 2.17 GHz Intel Pentium Dual CPU, 2 GB RAM and 150 GB hard disk. Python 3.0 was installed and HornMorpho, amharic text analyzer, was configured for the testing of the proposed model. Every text file has been saved with UTF-8 encoding system for unicode characters processing.

5.3 Data Collection

Feature level opinion mining and summarization techniques are evaluated on 484 reviews manually collected from hotel, university and hospital domains. The reason behind choosing these domains is the availability of many willing opinion holders. Features have been manually extracted from these reviews and the opinion words along these features were also manually determined and classified. These reviews were collected through the forms of appendix A, B and C. The experimental results will be discussed under section 5.4.

We have evaluated feature level opinion mining and summarization model from two perspectives: effectiveness of feature extraction and polarity determination of adjacent words. Nouns in each review are extracted as features. And the adjacent adjectives have been considered as opinion words during manual extraction.

5.3.1 Collecting Features Manually from the Reviews

The term feature throughout this paper is the prominent attribute or aspect or component or part of the hotel, university and hospital. We have collected features manually in order to know how many of these features can be identified by the system. It was some times challenging to identify a word as a feature. But this problem was solved by using an adjective, **ጥሩ,** before the word and if the phrase is linguistically acceptable, the word that was tested by this adjective is a feature. For instance, **ጥሩ አመራር.** This phrase is linguistically acceptable. Therefore, the word **አመራር** could be taken as a feature. In contrast to this, let us take the phrase **ጥሩ ህዝባዊ.** This phrase is linguistically unacceptable. So, we could not take the word **ህዝባዊ** as a feature. Accordingly, we have collected features manually from three domains as it was shown in the appendices E, F, and G. Table 5.1 shows number of features that was extracted manually from the three domains.

Table 5.1: Number of Features Extracted Manually from Different Domains

Domain	Number of Reviews	Total Number of different Features
Hotel	204	46
University	180	48
Hospital	100	44

These features will be compared with the number of features identified by both basic and full prototypes whose results are depicted in Table 5.3 and Table 5.4 respectively.

5.3.2 Determining polarity of adjacent words manually

When we say opinions along features we mean that the adjacent adjective, either to the left or to the right, of the identified features. During manual collection, we have considered only adjacent words that means not all adjectives were collected. These adjacent words were determined as opinion words along with their polarity. The number of manually determined opinion words have been checked against the number of opinion words that were determined by the system in order to see performance of our model in the determination of opinion words.

Proposed system have been consulting the lexicon in order to classify adjacent words along identified features under አዎንታ or አሉታ or ያልተለዩ. Adjacent words can be opinion words that exist in the lexicon or opinion words that do not exist in the lexicon or not opinion words. The system classifies both opinion words which do not exist in the lexicon and are not opinion words under ያልተለዩ field whereas positive opinionwords under አዎንታ and negative opinion words under አሉታ. Table 5.2 shows number of manually collected opinion words that are adjacent to extracted features.

Table 5.2: Manually collected opinion words adjacent to identified features.

Domain	**Number different Features**	**Number of adjacent words**		
		Total	**Left/Right side opinion words**	**Both sides which are not opinion words**
Hotel	46	275	193	82
University	48	170	105	65
Hospital	44	108	59	49

5.4 Experimental Results and Discussion

We have used Precision, Recall and F-measure metrics to evaluate the effectiveness of our approach.

Precision measures the number of correctly identified items as a percentage of the number of items which are identified (see equation 5.1). In other words, it measures how many of the items that the system identified were actually correct, regardless of whether it also failed to retrieve correct items. The higher the precision, the better the system is at ensuring that what is identified is correct.

$$\boldsymbol{Precision} = \frac{\boldsymbol{CorrectlyIdentified}}{\boldsymbol{Identified}} \qquad [5.1]$$

Recall measures the number of correctly identified items as a percentage of the total number of correct items (see equation 5.2). In other words, it measures how many of the items that should have been identified actually were identified, regardless of how many spurious identifications were made. The higher the recall rate, the better the system is at not missing correct items.

$$\boldsymbol{Recall} = \frac{\boldsymbol{CorrectlyIdentified}}{\boldsymbol{TotalNumberOfCorrectItems}} \qquad [5.2]$$

F-measure is a harmonic mean evaluation measurement, which combines both recall and precision (see equation 5.3).

$$\boldsymbol{Fmeasure} = \frac{\boldsymbol{2 * Precision * Recall}}{\boldsymbol{Precision + Recall}} \qquad [5.3]$$

We have conducted two experiments in order to evaluate performance of the techniques we have employed. The first experiment is based on the general linguistic rule regarding position of the adjective words. Unlike adverbs, which often seem capable of popping up almost anywhere in a sentence, adjectives nearly always appear immediately before the noun that they modify [5, 17]. The second experiment is based on the stated general rule and an adjective which comes after a noun to modify it. In both experiments, context valance shifter words were considered. We have conducted two experiments to show performance differences between two methods. This is good for the beneficiaries to choose either the first or the second method.

5.4.1 First Experiment

Experiment one is based on pattern 1 and 2 of Section 4.2.5. We have used reviews collected from the three domains to evaluate this method. The prototype we have developed and applied for testing it was named as basic system. Table 5.3 depicts the evaluation results of experiment one.

Table 5.3: Evaluation Results of the First Experiment

Perspectives	**Domain**	**Manually Identified**	**Identified by basic system**	**Correctly Identified by basic system**	**Metrics**		
					Precision	**Recall**	**F-measure**
Features Extraction	Hotel	46	10	10	1	0.217	0.357
	University	48	15	14	0.933	0.292	0.445
	Hospital	44	13	12	0.923	0.273	0.421
				AVERAGE	**0.952**	**0.261**	**0.408**
Left/Right side opinion words determination	Hotel	193	175	138	0.789	0.715	0.750
	University	105	92	73	0.793	0.695	0.741
	Hospital	59	46	35	0.761	0.593	0.667
				AVERAGE	**0.781**	**0.668**	**0.719**

5.4.2 Second Experiment

Experiment two is based on all patterns of Section 4.2.5. Reviews collected from the three domains were also used for experment two. The prototype we have developed and applied for testing it was named as full system. Table 5.4 depicts the evaluation results of experiment two.

Table 5.4: Evaluation Results of the Second Experiment

Perspectives	Domain	Manually Identified	Identified by full system	Correctly Identified by full system	Metrics		
					Precision	Recall	F-measure
Features Extraction	Hotel	46	19	16	0.842	0.348	0.492
	University	48	22	17	0.773	0.354	0.486
	Hospital	44	18	14	0.778	0.318	0.451
				AVERAGE	**0.798**	**0.340**	**0.476**
Left/Right side opinion words determination	Hotel	193	221	180	0.818	0.933	0.871
	University	105	118	98	0.831	0.933	0.879
	Hospital	59	72	54	0.750	0.915	0.824
				AVERAGE	**0.800**	**0.927**	**0.858**

5.4.3 Discussion

Table 5.3 and Table 5.4 show the expermental results for the effectiveness of proposed model in extracting features and determining polarity of opinion words along identified features for the hotel, university and hospital domains.

The result under experment one, Table 5.3, shows the performance of the first method. From the experment we could observe performance of 95.2% precision and 26.1% recall in features extraction and 78.1% precision and 66.8% recall in the determination of opinion words. From the result, we can also say features displayed to the users are almost correct, 95.2% precision. This means, from 484 collected reviews 38 features were identified by the basic system in which 36 of them are correctly identified. In contrast to this, the recall of the first method in features extraction is low. This is because of the adjectives that come after the nouns were not considered. Around 138 features were manually identified from 484 reviews. Among these, only 36 of them were correctly identified which means around 102 features were not identified by the proposed method. Precision of opinion words determination is less by 17.1% when compared to the precision of features extraction in the basic system.

On the other hand experment two, Table 5.4, shows the performance of the second method. In the second method adjectives that come after and before nouns were considered. Polarity changer words are also considered. From the result, the recall in the first method becomes higher due to the features and opinion words that were ignored by the basic system could be considered by the full system. That means in the first method there were some features that were not extracted due to lacking left side adjective. But in the second method some of these features were extracted because of having adjective at their right side, these features coccur two or more than two times throughout the reviews. Accordingly, recall of features extraction in the first method, 26.1%, is raised to 34% in the second method. In fact precision of the second method in feature extraction is 79.8% which is down by 15.4% when compared to the first method. This is because of the system that we have used, HornMorpho, which tags both adjective and noun as a noun class. As a result some adjectives that are followed by an adjective two or more than two times could be extracted as being features which decreases precision of the first method in the extraction of the features. Actually this problem also exists in the first method but the probability of extracting not real features in the second method is higher. Precision of opinion words determination increased by 1.9% and recall of opinion words determination by the first method, 66.8%, is raised to 92.7% by the second method.

Generally, precisions of the first method in features and opinion words determination are higher when compared to its recalls. Precision of feature extraction in the second method is lower when compared to the first method whereas precision of opinion determination and recalls of both features extraction and opinion determination are raised in the second method.

5.5 Summary

By using precision, recall and F-measure metrics, two experiments were conducted for the features extraction and opinion words determination. Accordingly, different performances are obtained: the second method performed better than the first. From the two experiments, we can say that our feature level opinion mining from opinionated amharic blog is performing in a very promising way.

Chapter Six - Conclusion and Future Works

6.1 Conclusion

After the invention of the web, one can post reviews using blogs. But it is very difficult for a human reader to find relevant sources, extract pertinent sentences, summarize and organize them into usable forms. An automated opinion mining and summarization system is thus needed.

Feature level opinion mining is the process of extracting aspects or attributes of the target object, identifying opinions along with the extracted aspects, determine their orientation and finally summarize the reviews by grouping multiple opinions along features. These problems can be solved using different techniques among which the hybrid of the rule based and statistical opinion mining approach is assumed to perform better than the rule based and statistical taken independently.

This research work came up with a design and prototype of feature level opinion mining from Amharic blog. Our feature level opinion mining model mainly consists of five components: Text Operator, Morphological analyzer, Feature extractor, Opinion extractor and Feature opinion summarization.

To evaluate the performances of the systems; we have collected 484 reviews from hotel, university and hospital domains. Then prototype of two versions, basic and full prototype system, were developed and precision, recall and F-measure were employed to evaluate features extraction and opinion words determination for both systems. Accordingly, 95.2 % average precision, 26.1% average recall for the features extraction and 78.1% average precision, 66.8% average recall for opinion words determination performances were obtained by the first method. The second method achieves an average precision of 79.8% and an average recall of 34% performances for features extraction and 80% average precision and 92.7% average recall for opinion words determination performances were obtained. The results show that this study is promising.

6.2 Future Works

In this research, an attempt is made to design and develop a feature level opinion mining model. Arriving at a full-fledged feature level opinion mining for the specified language is time consuming and involves coordinated team effort from computer science or information science and linguistic professionals that work on different levels and subcomponents. The following are some of the recommendations for further research and improvement:

- Different papers stated that there are two types of features: explicit and implicit. We have devoted to the extraction of explicit features. Extracting implicit features is also very important that we will consider in the future work.
- In this work, features have been used along with their affixes. Even though it has its own advantage in keeping the originality of opinion holders‟ expression, it may increases number of the features. Therefore, grouping the same features with multiple inflections to a common feature and grouping semantically similar features will be part of a future work.
- Opinion search and retrieval: Since the general Web search has been so successful in many aspects, it is not hard to imagine that opinion search will be very useful as well. For example, given a keyword query "**የአሊጋ ዋጋ**", one wants to find positive and negative opinions on the issue from an opinion search engine. This is a good idea to include it in the future work.
- As opinions on the web are important for many applications, it is not surprising that people have started to abuse the system. Opinion spam is a fake or bogus opinion that misleads readers by giving undeserving positive opinions to some target objects in order to promote the objects and/or by giving malicious negative opinions to some other objects in order to damage their reputations. Detecting such spam is very important for applications in the future work.
- In this work, we have considered nearby adjectives. In rare case, there are terms that can modify nouns by being far from it. We will consider these terms in the future work.

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Appendices

Appendix A: Questionnaire form for the hotel domain review collection manually

አዲስ አበባ ዩኒቨርሲቲ

በተፈጥሮ ሳይንስ ኮሌጅ፣ የኮምፒዩተር ሳይንስ ትምህርት ክፍል

<u>በሆቴል ተጠቃሚዎች የሚሞላ መጠይቅ</u>

<u>የመጠይቁ አላማ፡</u>

በአዲስ አበባ ዩኒቨርሲቲ በኮምፒዩተር ሳይንስ ትምህርት ክፍል ለማስተርስ ዲግሪ ምርምር ማሟያ የሚሆን በአማርኛ ቋንቋ ላይ መሰረት ያደረገ የሆቴሎችን አገልግሎት ለማሻሽል እና መረጃን ለማጠናከር ይረዳ ዘንድ ኮምፒዩተረይዝድ የሆቴል ተጠቃሚዎች አስተያየት መለያ ሲስተም ለመስራት ግብዓት የሚሆኑ አስተያየቶችን ለመሰብሰብ ነዉ፡፡

በቅድሚያ ለሚያደርጉልን ትብብር ከልብ እናመሰግናለን፡፡

የ ____ሆቴል ተጠቃሚ ኖት?

እንግዲያዉስ ሊደነቅ/ሊበረታታ እና ሊስተካከል የሚገባ የሆቴሉ አካል/ክፍል አጠር ባለ መልኩ ይግለፁልን፡፡

መልስ____
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<u>የመጠይቁ አዘጋጅ</u>፡ ቱሉ ጥላሁን በኮምፒዩተር ሳይንስ ትምህርት ክፍል የማስተርስ ዲግሪ ተማሪ፡፡

Appendix B: Questionnaire form for the university domain review collection manually

አዲስ አበባ ዩኒቨርሲቲ

በተፈጥሮ ሳይንስ ኮሌጅ፣ የኮምፒዩተር ሳይንስ ትምህርት ክፍል

በተለያዩ ዩኒቨርሲቲዎች እና ኮሌጆች ውስጥ ባሉ የማኅበረሰብ ክፍሎች

የሚሞላ መጠይቅ

<u>የመጠይቁ አላማ፡</u>

በአዲስ አበባ ዩኒቨርሲቲ በኮምፒዩተር ሳይንስ ትምህርት ክፍል ለማስተርስ ዲግሪ ምርምር ማሟያ የሚሆን በአማርኛ ቋንቋ ላይ መሰረት ያደረገ የዩኒቨርሲቲዎች እና ኮሌጆች አገልግሎት ለማሻሻል እና መረጃን ለማጠናከር ይረዳ ዘንድ የዩኒቨርሲቲና ኮሌጅ ተጠቃሚዎች አስተያየት መለያ ሲስተም ለመስራት ግብዓት የሚሆኑ አስተያየቶችን ለመሰብሰብ ነዉ።

በቅድሚያ ለሚያደርጉልን ትብብር ከልብ እናመሰግናለን።

ሊደነቅ/ሊበረታታ እና ሊስተካከል የሚገባ አጠር ባለ መልኩ ይግለፁልን።

መልስ____
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<u>የመጠይቁ አዘጋጅ</u>፡ ቱሉ ጥላሁን በኮምፒዩተር ሳይንስ ትምህርት ክፍል የማስተርስ ዲግሪ ተማሪ።

Appendix C: Questionnaire form for the hospital domain review collection manually

አዲስ አበባ ዩኒቨርሲቲ

በተፈጥሮ ሳይንስ ኮሌጅ፣ የኮምፒዩተር ሳይንስ ትምህርት ክፍል

የተለያዩ ሆስፒታሎች እና ክልኒኮች ተጠቃሚ

የሚሞላ መጠይቅ

<u>የመጠይቁ አላማ፡</u>

በአዲስ አበባ ዩኒቨርሲቲ በኮምፒዩተር ሳይንስ ትምህርት ክፍል ለማስተርስ ዲግሪ ምርምር ማሟያ የሚሆን በአማርኛ ቋንቋ ላይ መሰረት ያደረገ የሆስፒታሎች እና ክሊኒኮች አገልግሎት ለማሻሻል እና መረጃን ለማጠናከር ይረዳ ዘንድ የሆስፒታልና ክልኒኮች ተጠቃሚ አስተያየት መለያ ሲስተም ለመስራት ግብዓት የሚሆኑ አስተያየቶችን ለመሰብሰብ ነዉ፡ ፡

በቅድሚያ ለሚያደርጉልን ትብብር ከልብ እናመሰግናለን፡፡

ሊደነቅ/ሊበረታታ እና ሊስተካከል የሚገባ አጠር ባለ መልኩ ይግለፁልን፡፡

መልስ____

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<u>የመጠይቁ አዘጋጅ</u>፡ ቱሉ ጥላሁን በኮምፒዩተር ሳይንስ ትምህርት ክፍል የማስተርስ ዲግሪ ተማሪ፡፡

Appendix D: Sample reviews that were posted on the blog

Appendix E: Manual features and number of opinion words for the hotel domain

Manual Features	Number of Left/Right Opinion words	Manual Features	Number of Left/Right Opinion words
አልጋ	4	ዘገምተኛ	0
አገልግሎት	33	ዳንስ	0
አመራር	0	ደረጃ	0
ነገር	13	ስምምነት	0
ምሳ	0	አድናቂ	0
ፎቅ	0	ጭንቅላት	0
ማቆሚያ	2	ጥበቃዉ	1
ሰረተኞች	3	ክፈሎች	1
ሆቴል	17	አሙቺ	0
ሰረተኞቹ	3	ሰረተኛ	0
ሬስቱራንቱ	1	ታማኝ	0
ሰርቪሳቸዉ	0	ምግብ	38
ዋጋ	3	ጋርደኑ	1
ምግባቸዉ	3	ጋርደን	2
አገልግሎታቸዉ	4	መኪና	1
በለቤት	1	ዌይተሮች	0
ዌይተሮቹ	4	ቦታ	19
ላዎንጅ	1	ሬስቱራንታቸዉ	1
ክፍል	0	መኝታ	6
ቡና	1	ጫማ	1
ኢንተርኔት	0	እንግዳ	1

Appendix F: Manual features and number of opinion words for the university domain

Manual Features	Number of Left/Right Opinion words	Manual Features	Number of Left/Right Opinion words
ግቢው	3	ፕሮክተር	4
ሞዴል	0	ሬጅስትራር	2
ካፌ	7	ፈጣን	1
አገልግሎት	4	ግንኙነት	4
አመራር	5	ተማሪ	0
ግቢ	1	መጸዳጃ	0
ቤት	0	ካፌዎች	0
ህክምና	1	ካፌዎቹ	1
ፈተና	0	መታወቂያ	0
ፀኃፊዎች	3	ትምህርት	1
ማምህራን	18	ኳስ	0
ቦታ	0	ኢንተርኔት	2
ሬጂስትራር	3	ስፖርት	0
መናፈሻ	1	ሜዳ	2
ዘበኛ	7	ምግብ	2
ገቢ	0	ፖሊስ	1
ቲከር	7	ዶርም	3
መዝናኛ	1	ግሊጋሎት	0
ላይብረሪ	8	ፀኃፊ	3
ዩኒቨርሲቲው	5	ማጠናከሪያ	0
ቲከሮች	1	ዋጋ	0
ዩኒቨርሲቲዉ	0	አለቃ	0

Appendix G: Manual features and number of opinion words for the hospital domain

Manual Features	Number of Left/Right Opinion words	Manual Features	Number of Left/Right Opinion words
ሽታ	1	ወላድ	0
አልጋ	3	ትምህርት	0
አገልግሎት	1	ሀኪሞቹ	0
ዘበኛ	2	ዘረኛ	0
ቤት	5	ዶክተር	1
አዋላጅ	2	መድሀኒት	3
ምርመራ	1	ሆስፒታል	1
ህክምና	0	ሆስፒታሉ	4
ክሊኒክ	0	ሽንትቤቱ	1
ግቢ	2	ሽንትቤት	1
ድንገተኛ	4	መጸዳጃ	0
ላብራቶሪ	0	መልካም	0
በሽተኛ	0	እናት	0
ባለሙያ	4	ቦታ	3
ክፍል	4	መዝገብ	1
አመራር	3	አሰልቺ	1
ህሙማን	0	መኝታ	1
ታማሚ	0	ርካሽ	0
አስደሳች	1	ብዛት	1
ተመላላሽ	0	ጥበቃ	1
ሆስፕታል	1	ዋጋ	3
ፋርማሲ	3	በህሙማን	0

Appendix H: ከዚህ በታች የተዘረዘሩት 578 ቃላት አፍራሽነትን / አሉታን ያሳያሉ፡፡

ቂመኛ	ጉርምርምታ	አላግባብ	አርነት	አጥፊ
የማይመች	አለመሆን	ብስጭት	ፈት	መጫር
ነሁላላ		አለመተማመን	እለታዊ	ኢምንት
አክሳሪ	አለመሆኑ		ሲኦል	ሸባ
ትእቢት	ፍርሀት	ቀጣፊ	እብድ	ኋላቀርነት
እቡይ	ደረቅ	የሚያስቀይም	ደካማ	ትርምስ
ጮሌ	ቋጣሪ	እኩይ	ንፉግ	ገውጋዋ
ኢፍትሀዊ	መርዝ	የባሰ	በቀል	ልል
ዘራፊ	ጠባቦች	ፌዝ	አይደላም	የማይረባ
ደነዝ	የማይደላ	ቅጣት	ሽፍታ	ጉደኛ
ያልታወቀ	እድፍ	ከባድ	ወላዋይ	ሙጭጭ
ወገናዊ	ወሬኛ	ያለመሳካት	ቂል	ሀሰት
ህፀፅ	ጨፍጫፊ	ምላሽ	አሉታዊ	አሳሳች
ኢፍትሀዊነት	አልሆነም	በሽታ	ሻገተ	ወራዳ
እልሀኛ	አልተመቸኝም	ህቅታ	ቂም	ደመኛ
ተቃዋሚ	ጠላት	የተጋለጠ	ጥፋት	ችግር
መሸወድ	ዝንጉ	ወንጀለኛ	ያልነቃ	ክስ
የምያሳጣ	መንዛዛት	ተራ	የተዘበራረቀ	የሌለዉ
ተቃራኒ	መአት	ሌሊት	ምቀኛ	እርጉም
ጥገኝነት	ጨቅጫቃ	በሽተኛ	ጥፉ	አማፅያን
ብልጣብልጥ	ጦርነት	እርካሽ	ጥድፍያ	ሞልቃቃ
ጀልጋጋ	ተፃራሪ	ንጭንጭ	ተናደደ	ተፅእነኖ
አድካሚ	ቅሬታ	ቸልተኛ	ፈዛዛ	ማታለል
መቅጫ	ኡኡታ	ወረርሽኝ	ሰነፍ	ጠብ
ግፈኛ	ቀውስ	ያ ልነቃ	ቅጥፈት	ስንኩል
ጨለምተኛ	አረንቋ	አጭር	ሽበት	ጉዳት
አነካ ኪ	ዉድ	አዋረደ	አይታዘዙም	ኮ ርማታ
	አፍራሽ	ባዶ	መከራ	አማፂ
እዳ	ወለፈንድ	ከረከረ	የማይስማማ	ንፍግ
እምባ		አስጠያፊ	ሽብርተኛ	ብልሹ
ባርነት	ሞልጣፋ	ረብሻ	ባእድ	ውሻ
ነዳይ	አንገብጋቢ		አስጠሊ	ሳፋሪ
ፈተና	የሞተ	እንቅፋት	ጉረኛ	ጥል
ወልጋዳ	ጩሀት	ምፀት	ከሀዲ	ቅናት
ገዳይ	ግድፈት	ያረጀ	ነቀፋ	ሀጢአት
ቱባ	ስርቅታ	የማይታለም	ተጠራጣሪ	አልባሌ
እብለት	የሚያስጠላ	የማይል	ዱርዬዎች	ነፃነት
መዘዝ	ዝቃጭ	ቀማኛ	እርቃን	ቅናታም
ወቀሳ	መና	ለፍላፊ	መቃወም	ሰይጣን
እሪታ	ዝሙ ት	የማይገኝ	ሰለባ	ስጋት
መልቲ	አጣዳፊ	አለመስማማት	ስድ	ያልተገደበ
በዘፈቀደ	ሀሜት	ገደብ	ዝሙት	ሰነፍ
ጭቅጭቅ	ግፊት	ድንጋጤ	ተንኮል	ሽክም
እንከን	ውርጅብኝ	ተመፃዳቂ	ቁስል	ህመም
አለቅጥ	ፍጥጫ	እከካም	እጦት	አንዛራጭ
አስደንጋጭ	በጎሪጥ	ዝርክርክ	አበሳ	መቅዘፍት
ኮተታም	አይደለም	የሚቃወም	ድባቅ	ካልቾ
ዱብዳ	ሌባ	ግፍ	አጠራጣሪ	ፈጣጣ
የማያስደስት	አስከፊ	ከንቱ	ሽንፈት	አድላዊ
የሚያበሳጭ	ዘግናኝ	አንጎል	ውስን	ምስኪን
ለቅሶ	አረመኔ	ቅማላም	ጅል	አምባገነን
ፈሳም	ዱርየ	አክራሪ	ትንሽ	ዘረኛ
ስሜታዊ	አስቸካይ	መጋኛ	ብኩን	ይጎላል

ንዝንዝ
መግረፍያ
ቆራጣ
ከፉ
እስከነአካቴው
ግርፍያ
ቅር
ልቅ
ያለአግባብ
አይልም
ገብጋባ
ጥለኛ
ኮተት
ማግለል
ጭንቅ
አይዴሉም
ውዥምብር
ሴራ
ዜሮ
ወንጀል
ወረኛ
ኋላቀር
ጠባሳ
አይመችም
ግትር
ከፋፋይ
አዳሚ
ዳተኛ
ጥቁር
ጠሳ
ጉስቁል
እርኩስ
ሀሴት
አያዉቁም
አላስፈላጊ
ማደናቀፍ
ወረተኛ
ይረብሻል
መደናገር
አጭበርባሪ
ንጭጭ
ማጭበርበር
ሽባ
ስድብ
አሸባሪ
ሞልፋግ
ቆሮ
ወከባ
ቦዘኔ
የተጋነነ
እንቆቅልሻዊ
አደገኛ
ጩኸት
ጥርሳም
አደናጋሪ
ፎጋሪ
ቅፅበታዊ
ያልተማሩ
አፋኝ
ክልክል
ሽፋፋ
ቂላቂል
አድማ
ጠባብ
ወሬ
ማንባት
ድንገተኛ
ጥፋተኛ
ልፍያ
ጥንታዊ
ሴሰኛ
አስቀያሚ
ነገረኛ
ቀልቃላ
ጎርባጣ
መቃብር
ትምክህተኛ
ጥገኛ
አመፅ
ደዌ
አሰቃቂ
አውደልዳይ
አደናቃፊ
ሹጣም
መጥፎ
ተልካሻ
እርግጫ
ትችት
ግራ
ኩራተኛ
ያልተረጋገጠ
ማስገደድ
ጥማት
ተመፅዋች
ደባሪ
ገገማ
ያልተገራ
የሚያሳፍር
አስመሳይ
ተመናመነ
ጋጠወጥ
ሽራፋ
መርዛም
ጥርጣሬ
ስርዝ
ስህተት
ቁርጠት
ሽረኛ
ነውጠኛ
ንደት
ብቸኛ
ወለብላባ
ማሸንክ
ጌጃ
ይሸታሉ
ጠማማ
ይጎላቸዋል
ጅንን
ይደብራል
ሞኝነት
ቅሌት
ጤናማጣት
ውስብስብ
አለመግባባት
የተጨናነቀ
ቡካን
ግርፋት
ፍዳ
ቀለጤ
ዬለዉም
ያበደ
የተሳሳተ
የማያረካ
ውሸት
ባለጌ
ብላሽ
የማየሻሻል
ያስጠላል
ባይሆንም
ሀሰተኛ
ሆዳም
አውዳሚ
ያልታጠበ
አስፈሪ
አፈንጋጭ
ፅንፈኛ
የሚያወላውል
ነፍጠኛ
ሞኝ
ዘዋሪ
ግጭት
ጣልቃ
የማይለወጥ
የሚያሳዝን
የሚያመነታ
መጮህ
ውርደት
ህገወጥ
አሰልቺ
ጋጋታ
ግም
ውሸታም
ማስጨነቅ
የሚረብሽ
ናፋቂ
ማጣት
መላምታዊ
አመል
መቅሰፍት
ጭፍጨፋ
ጅሎች
ፈሪ
ያልተዛባ
ፀፀት
አሉባልታ
መካን
ለምፍ
ምቅኝነት
ጭቁን
ኮስታራ
ጨላማ
ፋራ
ዝቅተኛ
ጎስቃላ
ልሞሾ
ሀዘን
ቀዥቃዣ
ባርያ
ምላሰኛ
ችኩላ
ቅልጣን
አታላይ
ቆሻሻ
ከይሲ
ክህደት
ችኩል
ቅፅበት
ፀያፍ
ግድያ
ሽካካ
ሳይሳካ
ግሽበት
ምስጢር
ፍጭት
ትምክህት
አድመኛ
ጥፊ
ከዳተኛ
ልግመኛ
ንትርክ
ሁከት
እጥረት
ህፍረት
መማቀቅ
እክል
መደብደብያ
ማስጠንቀቅያ
ችስታ
ሙጥኝ
ብቻ
አዛዥ
ሽብር
እምቢተኛ
ተፅእኖ
ፈርሳም
የሚያጎድል
ቁጣ
ነጭናጫ
ሎሌ
ጨካኝ
አፀያፊ
ቃጠሎ
ስስታም
አዋራጅ
የሚቃረን
ቀበጥ
ጭንቀት
ድሀ
ብድር
ድርቅ
ቅራኔ
ስደተኛ
ሙሰኛ
አስቸጋሪ
በደለኛ
ነውጥ
የማያምር
ቀሳፊ
ቀናተኛ
ትረባ
ዋልጌ
ድካም
ቀ ሽም
ኪሳራ
ተጠቂ
ሴረኛ
ረባሽ
እልቂት
ከሀድ
ሸርሙጣ
የማይታገስ
ጉ ድለት
ድንክ
ዘልዛላ
ውድመት
አቤቱታ
ያልሰመረ
ቀውላላ
ሚስጢር
ደብዛዛ
ሀራም
ተብታባ
ሀካይ
ዘገምተኛ
ድልዝ
ከውካዋ
ቅንጣት
ዬላቸዉም
የማይታመን
በደል

አስጨናቂ	ያልተጠበቀ	ስቃይ	የማይሰጥ	የተወናበደ
ጋኔን	ዘረኝነት	ዉሸታም	ጎሰኛ	ሂስ
ጥላሸት	ትእቢተኛ	መራራ	መንድስ	ብቸኝነት
በሊታ	ነፍናፋ	ለዘብተኛ	ጭንቅንቅ	ርካሽ
ባይሆን	መሀይምነት	መራር	ነዝነዛ	ኩምትር
ገሀነም	ድቃላ	ጥንብ	ድክመት	አይደለም
ይሉኝታ	ከሲታ	ብክለት	ጫና	
ነውር	የሚያስመሰግን	ፉንጋ	ሽሌ	

Appendix I: ከዚህ በታች የተዘረዘሩት 423 ቃላት አዎንታን ያሳያሉ፡፡

ገለልተኛ	ምርጥ	ማለፍያ	ፍቃደኛ	ውብ
ቆንጆዎች	ስንዱ	ደፋር	ተአምር	መግባባት
ጠንካራ	ዋስትና	ሞገስ	የላቀ	ቸር
የሚያበረታታ	የተካነ	ንቃት	ሞቅ	ልክ
ሀይማኖተኛ	ሰፋፊ	ቀልጣፋ	ጥቅም	የምደላ
በረከት	እሸሩሩ	ጥበብ	ትእግስት	ዘላቂነት
ባለሙያ	ድምቀት	ጥበበኛ	ፅኑ	ቁርጠኝነት
የምገርም	ትህት ና	ሰፊ	ሊጋሽ	ፈታኝ
እድገት	የደመቀ	አላቸዉ	ተመጣጣኝ	ባህላዊ
ፍቃድ	ደህና	ፍላጎት	ብርቱ	ተአማኒነት
ስልት	እርካታ	ንዋይ	አዝናኝ	በቂ
ነቃ	እሙን	ስጦታ	ራእይ	ድህነት
ተሀድሶ	የተወደደ	ጀግና	ዘንካታ	ሽልማት
ልማት	አርአያ	አለቃ	አስተዋይ	አወንታ
ተፈላጊ	ሎጋ	ብልጥ	ፐ	ስምምነት
ጤነኛ	ንፁህ	ወርቃ ማ	ብልህ	ፅዱ
እድለኛ	አንበሳ	ጣፋጭ	ያማረ	ዝምተኛ
ያለዉ	መልእክት	ቆንጆ	እውነተኛ	ልብ
ያለው	ትጋት	ጠቀሜታ	ጌጣጌጥ	አስፈላጊ
እሺ	ገቢ ራዊ	ታታሪ	ተሰጥኦ	ሲሳይ
ክብረት	ጠንቃቃ	ጥብቅ	አስደናቂ	የተስተካከለ
የበለጠ	እንቁ	ሀብት	አሳሳቢ	ቆራጥ
ግርማ	ተግሳፅ	መተዛዘኛ	ደንታ	ምስጋና
አንጠልጣይ	ባለውለታ	ህሊና	ተልእኮ	ጎሽ
ፈውስ	ጋባዥ	ፅናት	ጤና	አላማ
የምያዝናና	ሀይለኛ	ተድላ	ጎበዝ	የተመረጠ
ፀጋ	አወንታዊ	ጠቃሚ	ጠባ	ሽጋ
ፀፅታ	መሳካት	ሞያ	ጥሩ	ገናናነት
እምቅ	እድል	ታዋቂ	ልዩ	ፀባይ
አርአያ	ህጋዊ	ጣእም	ምቾት	አብነት
ማስወገድ	ርህራሄ	ቀኝ	ቁጥብ	ደህንነት
ቅልጥ	ወርቃማ	ጀብድ	ተጫዋች	ወሳኝ
ሳቂታ	እጣ	ቀሸት	ብልሆች	አስደማሚ
ሰናይ	ጭብጥ	እውቅ	የምያምር	ማስተዋል
ገነት	እፁብ	አስቂኝ	የምል	የበላይ
ነፃ	ብልሀተኛ	ስልጡን	ውል	ዋነኛ
ተነሳሽነት	አእምሮ	አሜን	መረጋጋት	ስብእና
መልካም	ጀግንነት	አስተማማኝ	እመርታ	ቅንጦት
ይቅርታ	ተመራጭ	ልምላሜ	አሸናፊ	ውድ
ሙደኛ	የሚበረታታ	ምሩቅ	ታጋሽ	ስልጣኔ
የማይካድ	ቅልጥፍና	ምክር	ተቀባይነት	ጥዱ
ቃል	ደስታ	ተአምራዊ	ስምም ነት	መታዘዝ

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Declaration

I, the undersigned, declare that this thesis is my original work and has not been presented for a degree in any other university, and that all source of materials used for the thesis have been duly acknowledged.

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Date: __________________________

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