ASPECT-BASED SENTIMENT ANALYSIS FOR AMHARIC AND ENGLISH COMMENTS FROM ETHIO TELECOM FACEBOOK AND TWITTER PAGES USING DEEP LEARNING

A Thesis presented

By

Wudie Abawa Hunegnaw

to

The Faculty of Informatics

Of

St.Marry's University

In Partial Fulfillment of the Requirements

For the Degree of Master of Science

in

Computer Science

January, 2025

Addis Ababa, Ethiopia

ACCEPTANCE

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Declaration

Sentiment Analysis on Amharic and English User Comments from Ethio Telecom's Facebook and Twitter Pages using deep learning

I. The undersigned, declare that thesis work is my original work ,has not been presented for a degree in this or any other universities, and all sources of material used for the thesis work have been duly acknowledged..

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This thesis has been submitted for examination with my approval as advisor.

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Abstract

A vital tool for comprehending public opinion in a variety of fields, such as customer service and business decision-making, is sentiment analysis. In this study, user comments from Ethio Telecom Facebook and Twitter pages in both Amharic and English are analyzed for sentiment. The primary aim is to classify these comments into distinct sentiment categories such as positive, negative, or neutral, providing actionable insights to improve customer satisfaction and service delivery. This work was to develop a bilingual sentiment analysis model using written comments from Ethiopian telecom platforms on Facebook and Twitter in both Amharic and English

To address the unique linguistic and morphological challenges of Amharic, the study incorporates specialized preprocessing steps, tokenization methods, and embedding's. A balanced dataset of annotated comments in both languages is compiled for training and evaluation. The results demonstrate the effectiveness of deep learning models in capturing sentiment across both languages, achieving high accuracy and robustness. A total of 13,389 comments were collected, preprocessed, and manually labeled. In terms of language distribution, 52.91% (7,084 comments) were in pure Amharic, 28.75% (3,850 comments) in pure English, and 18.34% (2,455 comments) were mixed-language comments. Data sampling techniques, feature extraction using word representation techniques like Word2Vec, GloVe, and FastText, and deep learning architectures like Long Short-Term Memory networks (LSTMs) and Gated Recurrent Units (GRUs) were all used in the study. Metrics like accuracy, precision, recall, and F1-score were used to evaluate the models, and by achieving an accuracy of 74.38% and an F1-score of 74.12% in the train test split, LSTM was the best performer. While GRU models showed lower performance with accuracies of 73.67% and an F1-score of 70.62% in the 80% training and 20% of the dataset test set. The LSTM model demonstrated the most consistent and robust performance train-test splitting methods, making it the best choice for this bilingual sentiment analysis task. Based on these experimental results, the LSTM model with train test split is recommended for analyzing the sentiment of bilingual social media comments, ensuring consistent and generalizable results.

.***Keywords***: *Lexicon Sentiment Analysis, Deep Learning, Code, Social Media, Multilingual Sentiment Analysis, Ethio Telecom*

Table of Contents

DECLARATION III

ACKNOWLEDGMENT IV

LIST OF EQUATIONS IX

1.1.1 Background History of Ethio Telecom *2*
1.1.2 Ethio Telecom Services and Products *3*
1.1.3 Ethio Telecom social media *4*
1.1.4 Motivation of the Study *5*
1.2 STATEMENT OF THE PROBLEM 6
1.3 RESEARCH QUESTIONS 7
1.4 OBJECTIVE 7
1.4.1. General objective *7*
1.4.2 Specific Objective *7*
1.5 SCOPE AND LIMITATION OF THE RESEARCH 8
1.6 SIGNIFICANCE OF THE RESEARCH 8
1.7 ORGANIZATION OF THE THESIS 9

CHAPTER TWO 11

LITERATURE REVIEW AND RELATED WORKS 11

2.1 GENERAL OVERVIEW 11
2.2 LANGUAGES 11
2.2.1 Amharic Language *11*
2.2.2 English Languag *14*
2.3 SOCIAL MEDIA 14
2.3.1 Twitter *15*
2.3.2 Facebook *15*
2.4 SENTIMENT ANALYSIS (SA) 16
2.5 LEVELS OF SENTIMENT ANALYSIS 17
2.6 SENTIMENT ANALYSIS EVALUATION METHODS 18
2.8 ARTIFICIAL NEURAL NETWORKS 19
2.9 FEED FORWARD NEURAL NETWORK 20
2.10 MULTI-LAYER PERCEPTRON (MLP) 21
2.11 CONVOLUTION NEURAL NETWORK (CNN) 22
2.12 RECURRENT NEURAL NETWORK (RNN) 22
2.13 RELATED WORKS 25
2.13.1 Neural Network Based Sentimental Analysis *27*

CHAPTER THREE 30

RESEARCH METHODOLOGY 30

3.1 INTRODUCTION 30
3.2 PROPOSED MODELS OF RESEARCH METHODOLOGY 30
3.3. DEVELOPMENT SOFTWARE AND HARDWARE TOOLS 32
TABLE3. 1 DEVELOPMENT TOOLS AND LIBRARIES 32

3.4 DATA COLLECTION....35
3.4.1 Dataset Description and Characterization of the Collected Data 36
3.4.2Dataset Description of Language and Polarity Distribution....37
3.5 DATA PREPROCESSING AND CLEANING 39
3.5.1 Noisy Data Cleaning....39
3.5.2 The Punctuation, Numbers and Special Symbols Removal....39
3.5.4 Stop-word Removal 42
3.2.1 Tokenization....43
3.5.6 Other Preprocessing and Cleaning....43
3.5.7 Negation Word Handling....43
3.6 WORD REPRESENTATION 44
3.7 MODEL DEVELOPMENT....44
3.8 MODEL EVALUATION 44

CHAPTER FOUR 47

EXPERMENTS, RESULTS AND EVALUATION 47

4.1 IMPLEMENTATION OF THE PROPOSED SOLUTION 47
4.2 DATA SAMPLING METHODS IN DEEP LEARNING....50
4.3 FEATURE EXTRACTIONS EXPERIMENT....51
4.4 DISCUSSION OF EXPERIMENTAL RESULTS....52

CHAPTER FIVE....54

CONCLUSION AND FUTURE WORKS 54

5.1 INTRODUCTION 54
5.2 CONCLUSION 54
5.3 RECOMMENDATIONS AND FUTURE WORK 55
APPENDIX I: SAMPLE OF DATASET....64
APPENDIX II: SAMPLE OF PYTHON CODES 64
#Python Code to remove punctuation, numbers, and symbols 64
#Python Code stop word removal 65
#Python Code English Word level normalization 65

LIST OF TABLES

TABLE 2. 1 SUMMARY OF NUMBERS, CHARACTER AND PUNCTUATION MARKS IN AMHARIC SCRIPT........... 20

Table 2. 2 Comparative of Analysis Techniques on Sentiment Analysis…………………..28

Table3. 1 Development Tools and Libraries……………………………………………… 28
TABLE3. 2 DATASET DESCRIPTION.. 28
TABLE3. 3 ETHIO TELECOM SOCIAL MEDIA REVIEW (FACEBOOK DATA) SAMPLES.................................... 26
TABLE3. 4 TOTAL CLEANED DATASET DESCRIPTION.. 376
TABLE3. 5 TOTAL DATASET DESCRIPTIONS OF LANGUAGE DISTRIBUTION.. 377
TABLE3. 6 TOTAL DATASET POLARITY CLASS DESCRIPTIONS.. 388
TABLE3. 7 SAMPLE OF DATASET (COMMENTS) IN LANGUAGES... 39
TABLE3. 8 CONFUSION MATRIX.. 45

List of Figure

FIGURE 2. 1 EXAMPL OF ARTIFICAL NEURONS……………………………………………20
FIGURE 2.2 FEEDFOWARD NEURALNETWORK ARCHITECTURE……………………………………………………………21

Figure2. 1 The internal structure of long short-term memory ………………………………………………………23

Figure2.4 Bidirectional-LSTM………………………………………………………………..25

Figure3.1 General Architecture of the Proposed Model……………………………………………………………..25

Figure3. 1 Amharic character normalization…………………………………………………………………………….41

FIGURE 3. 4 REPEATED CHARACTER NORMALIZATION 35
FIGURE 3. 6 STOP WORD REMOVAL 36

List of Equations

EQUATION 3. 1 :ACCURACY 45
EQUATION 3. 2 :PRECISION.. 46
EQUATION 3. 3: RECALL 46
EQUATION 3. 4 F1 SCORE 47

ACRONYMS AND ABBREVIATIONS

2G	Second Generation
3G	Third Generations
4G	Fourth Generations
API	Application Programming Interface
BOW	Bag of Words
CA	Classification Accuracy
CDR	Call Detail Record
CRM	Customer Relation Management
DWDM	Dense Wavelength Division
Multiplexing ETA	Ethiopian Telecommunications
Authority ETC	Ethiopian Telecommunication
Corporation F1	F-Score/ F-Measures
FDRE	Federal Democratic Republic Of
Ethiopia GTP	Growth Transformation Plan
IBTE	Imperial Board Of Telecommunications Of
Ethiopia K-NN	K-Nearest Neighbor
LSTM	Long Short-Term Memory
CNN	Convolution Neural Network
MCIT	Ministry of Communications & Information Technology
ML	Machine Learning
MLP	Multi-Layer Perceptron
NGN	Next Generation Fixed
NLP	Natural Language Processing
PT and T	Ministry Of Post, Telegraph and Telephone
PTT	The Central Office Of Post, Telegraph and
Telephone ReLu	Rectified Linear Unit
SA	Sentiment Analysis
SNN	Simple Neural Network
SOV	Subject-Object-Verb
SVM	Support Vector Machines
TF-IDF	Term Frequency-Inverse Document
Frequency UTF	Unicode Transformation Format
VAS	Value Added Service

RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory networks
GRUs	Gated Recurrent Units
ABSA	Aspect-Based Sentiment Analysis

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Natural Language Processing (NLP) has evolved as a critical field within computer science, enabling machines to process and interpret human language[1]. Sentiment Analysis (SA), a subfield of NLP, is widely applied across industries to gauge public opinion on products, services, and societal trends. With the rise of social media, organizations like Ethio Telecom can extract valuable insights from user-generated content.[2]

To determine the customers or opinion holder's attitude and perceptions regarding certain subjects, goods, services, or the document's overall contextual polarity, sentiment analysis on social media is also necessary. It controls the subjectivity of whether an expression is positive or negative by using automated methods to identify the polarity expressions of opinion holders. [3]. It considers the entire article to be one basic informational unit that covers a single topic. Sentences are categorized as neutral, negative or positive at the sentence level. On the other way, aspect-level sentiment classification uses the traits or features of the sentences or documents to categorize them as neutral, negative, or positive[1].

The term "Big Data" describes datasets that are too large for standard database software tools to handle, store, capture, and analyze. Additionally, the three main characteristics of volume, variety, and velocity are used to define big data in general. Variety refers to data created from a variety of sources and in different formats, while volume refers to the amount of data that takes up a significant amount of storage space. Velocity is a measure of how frequently data is generated from various sources. Numerous industries, including telecommunications, healthcare, education, and finance, have made extensive use of big data analysis, especially social media data analysis, to improve business decisions, streamline operations, increase profitability, and satisfy customers[2][3]. The most widely used platform for people to express their opinions, thoughts, and information about a variety of subjects, goods, and services offered by different companies now a days is social media.[4]

Social media can be used by businesses and enterprises for a number of purposes, such as communicating with customers, learning about their needs, and creating new products and services through social media engagement[4]. Sentiment analysis is an effective method for identifying the positive, negative, and neutral polarity of written opinions. Sentiment analysis often begins with a lexicon of both positive and negative words and phrases. These lexicons assign labels to entries based on their previous polarity[3][4].

1.1.1 Background History of Ethio Telecom

For around 130 years, Ethio telecom service provider has been Ethiopian Telecommunications Corporation (ETC), now known as Ethio Telecom. Previously called the Ethiopian Telecommunications Corporation (ETC), Ethiopian Telecom is the country's top provider of phone and internet services. In Ethiopian telecommunications history, Emperor Menelik II initially introduced telephone services in 1894. They were building a telephone line from Harar to the capital, Addis Ababa. The interurban network then continued to expand satisfactorily in all other directions from the capital. Long-distance communication was possible because many of the Empire's major centers were connected by lines. Between the parties making the calls, operators or assistants at intermediate stations frequently acted as human verbal repeaters. During that time, Ethiotelecom went through multiple stages of rebranding and restructuring[5].

First, from 1890 to 1907, the service was run under the auspices of the "Central Administration of Telephone and Telegraph System of Ethiopia," which was a division of the Imperial Court of Menelik II. Between 1907 and 1909, the service was renamed "The Central Office of Post, Telegraph and Telephone (PTT) System of Ethiopia." The Ministry of Post, Telegraph and Telephone (PT and T)" was the new name given to the service in 1910. The Ethiopian telecoms company was renamed "The Provisional Military Government of Socialist Ethiopia Telecommunication Services" in October 1975 under the Dergue dictatorship. In January 1981," It continued to be known as ETA until November 1996. During this time, there was a significant technological shift in the telecommunications sector, moving from automatic to digital expansion.[6]

The Federal Democratic Republic of Ethiopia restructured the telecom sector and established two separate, autonomous entities, the Ethiopian Telecommunications Authority (ETA) and the

Ethiopian Telecommunications Corporation (ETC), by issuing Proclamation Number of 49/1996 in November 1996. After focusing on agriculture, health, and education in the 2005/06-2009/10 five-year plan, the Ethiopian government has decided to focus on enhancing communications services. Ethiopian Telecom was founded on Monday, November 29, 2010, with the goal of improving telecommunications services for the benefit of health, education, and agriculture as a key development lever. The Growth Transformation Plan (GTP), which has high goals for the year 2015, stems from this desire to promote our nation's stable growth. According to the corporation, Ethio telecom must simultaneously offer all residents ubiquitous, reasonably priced service and access, as well as cutting-edge services to those individuals, organizations, and enterprises that require them. The business aims to provide top-notch customer service to support those services. Ethio Telecom's goal is to simplify life and hasten Ethiopia's digital transformation by offering dependable communications and digital.

1.1.2. Ethio Telecom Services and Products

Mobile telephony, also known as cellular mobile services, comprises a variety of mobile telecom services, such as voice services, voice and non-voice messages, short message, and data services. Other telecom services include (i) fixed telephony, (ii) broadband access, and (v) mobile money, also known as telebirr. In other words, telecom products include mobile phones, modems, internet cables, financial services, and various telephony services that are offered by telecom businesses[7].

Ethiopian telecom began offering long-distance phone communication with a help operator in 1894. The business then began providing telegraph service from Dire Dawa to Djibouti in 1906.

In 1952, service of radio stations installed for international and domestic telecom services. From the year of 1979, international communication launched through Sululta Earth Satellite Station.

In 1988, digital exchanges and telecom services were installed starts services. Besides digital exchange in 1989, digitalmicrowave & fiber cable communication systems were started[8].

Internet service was first offered in 1997, while mobile service was established in 1999. Dense Wavelength Division Multiplexing (DWDM), Third Generation (3G), Next Generation Fixed

(NGN), and networks based on optical fiber transmission were introduced and services began in 2007. In 2015, the business introduces 4G/LTE mobile technology for the first time in Addis Ababa, Ethiopia also 5G start and expands .

Under the brand name "tele birr," the mobile money company was established on May 11, 2021, with the goal of providing the greatest mobile money solutions to our esteemed clients and the community at large. We will put extra effort into offering financial services to individuals and those living without banking services. The business also formally introduced the cutting-edge 5G (fifth generation) mobile network for the first time in May 2022.

In addition to prepaid, postpaid, and hybrid SIM accounts, the Ethiopian telecom company also provides 3G and 4G (LTE) and VSAT services, mobile broadband by 3G and 4G (LTE), VPN services using 3G, 4G (LTE), and 5G, business mobile and internet, M2M business, fax, fixed wireless CDMA, fixed line service (ADSL), domain name service, mobile internet, roaming, mobile money, and mobile services.

1.1.3 Ethio Telecom social media

Anyone (individuals, companies, organizations, and so on) can interact with others or share information in real time through social media, an online communication tool. Businesses can use social media for a variety of reasons, including attracting customers, gathering feedback from customers, reaching a wider audience, cutting marketing expenses, boosting revenue through advertising and customer networks, building a company brand, enhancing business procedures, and keeping an eye on rivals[9].

With extensive plans in place to satisfy the demands put forth by the Ministry of Communications & Information Technology (MCIT) and the Ethiopian people, Ethio telecom today offers telecom services throughout the entire country. According to data from the first half of December 2023, Ethiopian Telecom has more than 74.6 million customers. Mobile Service Subscribers are over 71.7 million, data and Internet Users are over 36.4 million, Fixed Broadband users are over 688.3 thousand and Fixed Line Service Subscribers are over 834.1 thousand, from a few recent years Ethio Telecom joined different social media for different purpose to reach its customers mainly for advertising and promotion of its services[9].

Facebook, Telegram, Twitter, Instagram, LinkedIn, and its own website are just a few of the social media platforms where Ethiopian Telecom has followers. According to the sites from various social media platforms, Ethiopian Telecom has more than 1.3 million Facebook fans, over 34.8 thousand Twitter followers, and 32,314 LinkedIn followers as of December 2023[10].

1.1.4 Motivation of the Study

In the real world, businesses and companies use a variety of channels to post, tweet about goods and services. We now live in a customer-centric economy where the value of client opinion is highly established[11].

For this reason, getting input from customers is more crucial than ever. For businesses and organizations looking to establish their own strategies and learn how customers react to products, services, and branding, customer feedback is extremely valuable[12][13]. Textual facts are the most pertinent and easily readable of various forms of expressing emotions and opinions.

Social media users can utilize text to share their thoughts, feelings, and perspectives about a particular feature of businesses' goods and services.

Essential data is currently available for a number of uses, such as forecasting future product releases, obtaining consumer opinions about the brand, manufacturing companies, economic trends, and online social facts. However, social media data is challenging to use in nature because to its multilingualism, unstructured format, and lack of labeling. Using and analyzing this data aids in social media monitoring and gives many businesses a general idea of how the public feels about particular issues[14]. These days, Ethio Telecom uses information from Call Detail Records (CDR), Customer Relation Management (CRM), and surveys conducted through questionnaires and in-person interviews with a sample of people as data collection methods to gauge customer satisfaction with its brands, products, and services (including telecom services). The majority of businesses and organizations, like Ethio Telecom, have invested a significant amount of money in using consultants and surveys to learn about the opinions and sentiments of their customers regarding their brands, commodities, and services[15]. These days, it's crucial for businesses like Ethiopian Telecom to use social network data to evaluate their branding, goods, and services. Therefore, gathering and evaluating the large amounts of data generated by social networks facilitates the extraction of knowledge. Since opinions are at the heart of practically every human activity and are the primary determinants of people's behavior, sentiment analysis techniques are used in practically every business and social domain[16]. Sentiment analysis is particularly useful in the business sector, where it is used to measure consumer voice, brand reputation, online advertising, and online commerce. In order to extract knowledge from the vast amount of social media data generated by Ethiopian Telecom's diverse social media platforms, automated models must be developed[17][14].

1.2 Statement of the Problem

Social media is very significant in today's world for many reasons. Social media platforms are used by businesses, various companies, government agencies, and even private citizens for entertainment, promotion, and advertising as well as to express their thoughts. People's opinions on a range of issues can be found on social media in a number of different languages[18].

For instance, a lot of information in a number of languages, such as Amharic, Afan Oromo, Tigrigna, Somaligna, Awngi, and others, may be accessed on various social media platforms in Ethiopia. Afaan Oromo language social media data sentiment analysis, Awngi (Agew) language sentiment analysis, Tigrigna language sentiment analysis, and Amharic language social media data sentiment analysis are among the sentiment analysis and opinion mining projects that have been completed on Ethiopian language social media data. Language-mixed social media text incorporates vocabulary and grammar from multiple languages, which presents another difficulty for multilingual sentiment analysis[17]. The usage of brief, shortened social media data in the phrases offers another difficulty. Due to character limits, the same words can also appear in sentences in a variety of ways, particularly on Twitter data. These succinct social media statistics are widely used, well-known, and occasionally generated by social media users. This study's primary goal is to examine sentiment analysis of bi-lingual (Amharic and English language mixed data) social media data[19].

For some languages, like English, which are referred regarded as well-resourced languages, a number of ways and resources have been developed for opinion mining. Compared to English, Amharic has fewer resources and sophisticated opinion mining techniques. Lack of well-annotated datasets, the inaccessibility of computational resources such as lexicon word lists, and the presence of few or no subject-matter experts are the causes of the dearth of resource tools. Low-resource languages, such as Amharic, are still difficult because annotated materials and necessary NLP technology are not publically available[20]. The aim of this work was to develop a bilingual sentiment analysis model using written comments from Ethiopian telecom platforms on Facebook and Twitter in both Amharic and English[10].

1.3 Research Questions

Addressing the aforementioned issues, this study will investigate the following research questions[21]:

QR1. Which dataset is available for sentiment analysis of user comments from Ethio Telecom's Facebook and Twitter Pages?

RQ2. How the dataset will be prepared for the sentiment analysis of user comments from Ethio Telecom's Facebook and Twitter Pages?

RQ3. Which features are more relevant for user comments from Ethio Telecom's Facebook and Twitter Pages?

RQ4. How to design a deep learning model for sentiment analysis on user comments from Ethio Telecom's Facebook and Twitter Pages?

RQ5. How to evaluate performance of designed model.

1.4. Objective of the study

1.4.1. General objective

The main goal of this study is to improve bilingual sentiment analysis model for Amharic and English comments from Twitter and Facebook pages of Ethio telecom using deep learning in case of Ethio telecom products and services.

1.4.2 Specific Objective

This study explicitly aims to address the following lists under the specific objectives to accomplish aforementioned broad objectives.

1. To gather comments from ethio telecom Facebook and Twitter sites in both Amharic and English
2. To preprocess and clean mixed language social media comments for further analysis

3. To compile lexicon terms that are suitable for this lexicon sentiment study project (both for Amharic and English language positive and negative word lists).
4. To extract characters
5. To use mixed language social media data to create a sentiment analysis model
6. To assess how well the created deep learning algorithms perform

1.5 Scope and Limitation of the Research

SA of Ethio Telecom social media data regarding the company's goods and services has been the main idea of this study. Although Ethio telecom promotes its services and goods on a number of social media sites, focuses on data produced by the company's users, clients, and followers on Facebook and Twitter in both English and Amharic. This study has only used textual data as its starting point. Both subjective and objective classification is not included. The study process and classifies sentiment texts express Amharic and English, using only grammatically correct sentiment texts. Additionally, grammatically incorrect texts, slang, ideas expressed by images, music, videos, or other emotive symbols, as well as written comments, are not included in this study. Because Amharic is a low-resource language and there isn't enough time to create a rule to implement it, the main drawback is absence of available annotated corpus, grammar corrector, stemmer, and lemmatization tool or library. The absence of an Amharic text dataset in Ethio telecom is one of the study's other main weaknesses. As a result, only a very tiny dataset can be used by the researcher[22].

1.6 Significance of the Research

Accepting the opinions of other crucial to make logical decisions in the business world of today. When making decisions, people usually ask for recommendations and guidance from others. By asking for feedback on their products through both public and private channels of communication, businesses can gain a better accepting of people's opinions and preferences. As a result, monitoring the reputation of their brand, researching changes in public opinion over time, and assessing the effectiveness of marketing strategies are all beneficial[8]. Bilingual SA in Amharic and English is used in this work to categorize comments as neutral, negative, or positive [9]. This work's primary goal is to demonstrate how businesses like Ethiotelecom can leverage mixed social media data that is, data that is available in many languages from various social media sites. Categorizing the polarity of a given text or comment at various aspect levels is fundamental problem in multilingual sentiment analysis[11].

The objective of this paper is to conclude the separation of a certain comment regarding the services and goods that Ethio Telecom is now offering that was gathered from official social media sites. Additionally, before making choices, it will have the ability to automatically evaluate the sentiment of the great majority of collected reviews. As a result, this study might assist the Ethio Telecom provider in enhancing their offerings going forward. The research's findings can be used into the creation of a comprehensive opinion mining system for both English and Amharic. The study's ability to assist in developing a complete viewpoint that may be utilized in a mining method for any other Ethiopian language is another significant aspect of its importance. A major advantage for future research is that the study's findings can also be used as input data for recommender and opinion retrieval/search systems.

1.7 Organization of the Thesis

This paper is prepared into six chapters as follow:

Introduction: Classified into two sections: section one contains historical backgrounds of telecom sector in Ethiopia, Ethio Telecom backgrounds and social media of Ethio Telecom. The second section under this chapter introduces an overview of social media data sentiment analysis, problem of the study, objective and methods

Literature Review and Related Works: Contains conceptual reviews of related researches conducted to sentiment analysis on social media data and sentiment classification are discussed under this chapter. In addition to this, it contains an overview and different approaches are reviewed. Also under this chapter different related works on the topic of the sentiment analysis by using different approaches on the monolingual, bilingual and multi-lingual social media data from different platforms are deeply explained.

Research Methodology: defines the main architecture of bi-lingual sentiment analysis classification model development. In addition to this, implementation-related issues (pre-processing, lexicon and deep learning sentiment classification are explained).

Experiments, Results and Discussions: Contains the entire experimental results of the proposed models and different data preprocessing steps, lexicon classification experiments, and different deep learning algorithms experiments are presented within the result of evaluation for each experiment.

Conclusion and Future Works: Under this chapter conclusion, recommendations and future works of this research works are stated in this last chapter.

CHAPTER TWO

LITERATURE REVIEW AND RELATED WORKS

2.1 GENERAL OVERVIEW

Finding and describing concepts that are important to this study and outlining their relationships are the goals of a conceptual literature review. This chapter also discusses and reviews several sentiment classification techniques, sentiment feature extraction, sentiment analysis levels, and assessment techniques. It also includes a definition of sentiment analysis, a discussion of Amharic and English language usage patterns, and an overview of social media [55][36].

2.2 Languages

Since bilingual sentiment analysis (Amharic and English mixed languages) is the main focus of this study, a quick summary of the behaviors and overviews of the two languages is provided below[23].

2.2.1 Amharic Language

People who speak different languages around the nation can communicate with each other using Amharic, which is the official working language of the FDRE. More than 86 languages, classified as Semitic, Cushitic, Omotic, and Nilo-Saharan, are spoken in Ethiopia. The Southwest Semitic group's Afro-Asiatic language, Amharic, is most closely linked to the Geʿez (Ethiopic) language. Geez script, an ancient Ethiopian script, is the source of the Amharic language's unique alphabetic symbols, known as fidel/⊥ደል/, which are written from left to right and do not utilize capitalization. Ethiopian languages such as Amharic, Tigrigna, Guragegna, Awi, and Argoba are all written using Amharic characters or fidelis (Encyclopaedia Britannica, Inc.)[24].

There are 33 base alphabets and seven orders in the Amharic language, which add up to 231 syllables. There are also 51 more labialized letters, which add up to 282 characters known as fidel/ ፊደል/. Every Amharic alphabet has seven distinct syllabic forms, also known as orders, that correspond to phonemes, which are pairings of consonants and vowels. By using the vowel sounds (አ ኡ ኢ ኣ ኤ እ ኦ) that correspond to English vowels (a, u, i, a, e, i, o), respectively, the other Amharic fidels are universally generated from the first order, which is the base form.[25]

Table2. 1 Summary of Numbers, Character and Punctuation marks in Amharic Script

No	Type of Amharic Characters	Number of Symbols
1	Core characters (33 x 7)	231
2	Labialized characters(e.g. ሏ, ቧ, ሟ)	51
3	Amharic numbers	20
4	Amharic Punctuations	8
	Sum	**310**

There are redundant or duplicate alphabets in some Amharic fidels that have the same sound but a distinct structure. These fidels, which have identical sound but varying in alphabetic structures, are (ሀ፡ሐ፡ኀ፡ኸ), (ሰ፡ሠ), (ጸ፡ፀ), and (ዐ፡አ).[26]

Basic Features of Amharic language

Amharic Sentence (Word ordering): Amharic sentences have distinct word ordering than English sentences. Unlike English, which uses a subject-object-verb (SVO) word sequence, Amharic has a different grammatical structure. The structure of an Amharic sentence is Subject Object Verb (SOV), with the subject at the beginning, the object in the center, and the verb at the conclusion[27][20].

"I am a teacher" is an English sentence. SVO configuration

The sentence in Amharicis "እኔ. Sentence in English: "I teach." Structure of SVO

The sentence in Amharic is "እኔ መምህር ነኝ." Structure of SOV

In Amharic a single fidel or consonant can carry full text or message. Some example are as follows: ሺ /shi/ „thousand", ና /na/ „come", ያ /ya/ „that", ፓ /pa/ amazing", ማma/ „who" and ዉ /wa/ „notice".

Absence of capitalization: Amharic characters do not distinguish between capital and lower case, in contrast to Latin and other characters.

Duplicate or redundant alphabets: Amharic characters have duplicate or redundant letters and digits that share the same sounds but differ in structure. These fields, which have the same sound but different alphabetic structures and are used interchangeably, are (ሀ፡ሐ፡ኀ፡ኸ), (ሰ፡ሠ), (ጸ፡ፀ), and (ዐ፡አ).

Punctuation in Amharic: Amharic punctuation differs significantly from English punctuation. These include **(።)**, which is a full stop or period; (፧), which is a question mark; (፣), which is a comma; (፨), which is a paragraph separator; and so forth.

Even though Arabic numbers are still commonly used in Ethiopia today, Amharic numbers still retain their own characters and are utilized in a variety of contexts, such as the Ethiopian calendar, the Orthodox church, and more. The following are some instances of Ethiopian numbers that correspond to Arabic numbers:

1= ፩, 2= ፪, 3 =፫, 4 =፬, 5= ፭, 6= ፮, 7= ፯, 8 =፰, 9= ፱, 10 =፲, 20= ፳,

30=፴, 40 =፵, 50= ፶, 60= ፷, 70 =፸, 80 =፹, 90= ፺, 100= ፻, 1000= ፼

Challenges of Amharic language for Sentiment Analysis

Sentiment analysis in Amharic presents a number of difficulties. The following lists highlight the primary obstacles to SA identification in Amharic.

Negation handling in the Amharic comments/sentence is one of these challenges.

The grammatical richness of Amharic makes it more difficult to identify and extract opinion termsinsentimentanalysis.

There are redundant or duplicate characters or fidels in Amharic that have the same sounds but different structures. For instance, አመሠግናለሁ and አመሰግናለው are identical but have different characters. The detection and extraction of opinion terms from idiomatic speech presents another difficulty for Amharic sentiment analysis.

2.2.2 English Languag

English is related to the majority of other languages spoken in Europe and western Asia, ranging from Iceland to India, because it is a member of the Indo-European language family. The United States, the United Kingdom, Canada, Australia, Ireland, New Zealand, and several Caribbean and Pacific island nations all use English, which has its roots in England. In addition, it is the official language of Singapore, India, the Philippines, and numerous sub-Saharan African nations, including South Africa. Because English is the primary foreign language in the majority of other nations, it has gained the status of a global lingua franca[28].

The majority of the languages spoken in Europe and western Asia, from Iceland to India, are linked to English because it is a member of the Indo-European language family[18].

Basic Features of English language

English Alphabets: The Latin alphabet is used for the English language. The 26 letters that make up the present English alphabet are Latin in origin and come in both uppercase and lowercase forms. A, E, I, O, and U are the five vowels that make up the English alphabet; the other twenty-one lettersareconsonants.

Word sequences: The (usually) fixed word order of the English language is another powerful feature. The majority of English clauses follow the SVO word order. This indicates that the Verb comes before the Object, and the Subject comes before the Verb[17].

2.3 Social Media

The Oxford Dictionary defines a social media as a website or application that enables users to create and share information or participate in social networking. It can also be defined as online communication platforms that enable users to share information, engage in dialogues, and produce web content. Microblogging is one of the most well-known forms of social media. Microblogging is the practice of sharing brief postings or messages, along with a mix of instant messaging, with an online audience using microblogging sites like Facebook, Instagram, Twitter, and others. Anyone can use a microblog as a means of online broadcasting to communicate brief messages with a global audience[29][19].

2.3.1 Twitter

Twitter one of the greatest social networks and a quick and easy way to send brief posts, GIFs, article links, and videos. Each tweet can contain up to 140 characters. It offers a useful forum for users to express their thoughts and ideas on popular subjects[30]. Twitter's 140-character tweets and brief share posts make it a suitable place for sentiment research.

Twitter is a social networking service that has been formally known as X since 2023. It is among the most popular websites and one of the biggest social media networks in the world[11][31]. Users can like other users' content and share brief text messages, photos, and videos in brief posts called "tweets" (officially "posts"). In addition, the platform has a chatbot (Grok), job search, bookmarks, lists, communities, direct messaging, video and audio calling, and a social audio feature called Space [59]. The Community Notes feature allows users to vote on context that has been added by authorized users[6][14].

2.3.2 Facebook

Facebook is a social media and networking platform that is owned by the American technology company Meta. Its name comes from the Facebook directories that are frequently provided to American college students. Mark Zuckerberg founded it in 2004 along with four other Harvard College students and roommates, Eduardo Saverin, Andrew McCollum, Dustin Moskovitz, and Chris Hughes. At first, only Harvard students were eligible to join; later, other North American universities joined. Facebook has been allowing users to register as early as 13 since 2006, with the exception of a few countries where the minimum age. According to Facebook, there were nearly 3.07 billion monthly active users worldwide as of December 2023[32].

It is the most widely used networking sites and micro blogging platforms. As of 2021, it had over 2.9 billion monthly active members, making it a very successful social media network with a diverse readership. Facebook users can interact with friends, family, and even businesses that want to share their goods and services online by sharing text, photographs, photos, live videos, and animations[33].

Smartphones, tablets, and personal computers that have Internet access can all access Facebook. Following registration, users have the option to create a profile that contains private information about them [60]. They have the ability to share text, images, and multimedia with other users who have accepted their friend request or, depending on their privacy settings, with the general public. Additionally, users can join groups based on shared interests, edit messages sent within 15 minutes of sending them, communicate directly with one another using Messenger, and get updates on the activities of their Facebook friends and the pages they follow[10].

2.4 Sentiment Analysis (SA)

Natural language processing (NLP) has numerous uses and crucial to our daily lives. Machine translation, chatbots, speech synthesis and recognition, text extraction, text summarization, and sentiment analysis are a few examples of NLP applications. The terms sentiment analysis, opinion mining, opinion extraction, sentiment mining, aspect analysis, emotion analysis, and review mining are all interchangeable [12][1].

"Brand sentiment analysis, opinion mining of algorithmic classification of users' evaluations of a brand (as positive, negative, or neutral) in posts and comments" is how a Dictionary of Social Media defines sentiment analysis[23]. Textual data is regularly subjected to sentiment analysis in order to help businesses and organizations track, scale, and comprehend client requests. Sentiment analysis is used in many different fields, including as marketing to gauge consumer response to a new product or service and by social media users to ascertain the general consensus on a trending topic. Based on reactions to previous iterations of the product in various regions, it can also help producers plan the launch of new products. Opinion mining, also known as sentiment analysis, is a Natural Language Processing (NLP) activity that is generally used to determine the writer's feelings regarding a variety of topics, issues, goods, or services that are presented online through various posts or comments on various social media platforms[1][34].

2.5 Levels of Sentiment Analysis

Numerous sentiment analysis experts have looked into numerous methods for comprehending sentiment at various levels[35]. Sentiment analysis levels refer to the many stages of sentiment categorization, including document, sentence, word, and feature levels[34].

Document Level: The main objective of document-level sentiment classification is to ascertain if a document expresses neutral, negative, or positive sentiments overall. To capture long-range dependencies and contextual information throughout the entire manuscript, deep learning models. Using extensive datasets and pre-trained embeddings, these models increase performance by learning to represent the material in a way that represents its overall sentiment[25][36].

Sentence-level: This type of sentiment classification is concerned with determining if a given sentence is positive, neutral, or negative. Convolutional Neural Networks (CNNs) and Bidirectional LSTMs are two deep learning approaches that are used to capture the semantic subtleties of phrases. Even in the presence of intricate linguistic structures and contextual connections, deep learning techniques can better comprehend the context of each sentence by utilizing pre-trained language models such as BERT (Bidirectional Encoder Representations from Transformers)[27][19].

Feature-level: Also referred to as aspect-based sentiment analysis, feature-level sentiment classification seeks to pinpoint and extract particular characteristics or aspects that the opinion holder has commented on in a text, as well as ascertain the sentiment that goes along with each element. In this area, models such as BERT and its variations are very useful because they can manage the complex links between words and aspects, enabling accurate sentiment attribution to several aspects in a single sentence. By recording sentiments toward particular aspects, aspect-level sentiment analysis offers a more detailed perspective on sentiment, overcoming the shortcomings of document and sentence-level analysis[20].

Developments in Deep Learning: By creating models that can recognize complex patterns in text data, deep learning has completely transformed sentiment analysis. These models can be adjusted for certain sentiment analysis applications after being trained on enormous volumes of data, improving their comprehension and interpretation of sentiment at various levels[28][16].

Generally speaking, it can take place at different levels; the most well-known levels are document-, sentence-, and feature-level. By offering tools to collect precise and context-aware feelings towards many aspects inside a single sentence, deep learning has solved many of the drawbacks of older methods, especially in feature-level sentiment analysis. As a result, sentiment analysis tools have become more thorough and precise, able to comprehend the complex nature of human language and sentiment[37].

2.6 Sentiment Analysis Evaluation Methods

One component of deep learning algorithms that is used to assess the algorithm's performance is the evaluation methods. Accuracy, precision, recall, F1-score, and other metrics and methodologies are used to assess deep learning models for sentiment analysis. These measurements aid in assessing how well the models capture and categorize sentiments. Sophisticated methods like ablation studies, confusion matrix analysis, and cross-validation are used to optimize model performance and guarantee robustness across various datasets and applications

Accuracy is a measurement's degree of proximity to true values or to the appropriate values for that measurement. The frequency of correction predictions made by the classifier is what it is. The ratio of accurate forecasts to the total number of cases assessed is what it measures[5].

Precision: Determines the proportion of accurately forecasted positive observations to all of the initial predictions. Out of all the predicted patterns in a positive class, it calculates the proportion of correctly predicted positive patterns. The number of positives divided by the total number of positive predictions is known as precision.

Recall: Provide responses to the query, "How many of the true positive were recalled (found)?" Out of every positive example in the dataset, recall calculates the number of positive class predictions that were made. The model's measure accurately identifies true positives, or the percentage of positive patterns that are correctly classified.

F-measure, also known as F1-score, is a harmonic mean of recall and precision. It offers the path to a single metric that combines the qualities of recall and precision into a single figure. It uses the formula below to calculate the mean value between recall and precision.

2.7 Deep learning

Artificial neural networks are used in deep learning, a subset of machine learning, to extract knowledge from data. Inspired by the human brain, neural networks can be used to handle a wide range of issues, such as speech recognition, image recognition, and natural language processing [11].

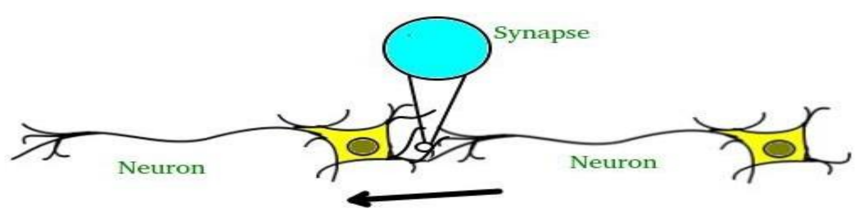
Deep learning is a branch of machine learning that makes use of algorithms that are modeled after the composition and operations of the human brain. Neural network-based models used in deep learning are called artificial neural networks (ANN) [29]. In a nutshell, artificial neural networks are computer systems that draw inspiration from the neural networks found in the brain. These networks are composed of a group of interconnected elements called artificial neurons, or just neurons. A signal can be transmitted from one of these neurons to another by any link, and the receiving neuron will then process it. Artificial neurons, or simply neurons, are a group of interconnected units that make up these networks. Every one of these connections has the ability to transmit a signal from one neuron to another, which the receiving neuron then processes. It then communicates with its downstream neurons, which are often arranged in layers. Various transformations can be applied to the inputs and outputs of different levels. Proceed from the input layer, which is the first layer, to the output layer, which is the last layer. Hidden layers are[37].

2.8 Artificial Neural Networks

The "artificial neural network" (ANN) is the most widely used and fundamental method of deep learning. They are brain-inspired systems made to resemble human learning. Artificial neurons, which are a group of interconnected units or nodes that roughly mimic the neurons in a human brain, make up an ANN. The human central nervous system contains cells called neurons. The connecting areas between axons and dendrites are called axons and dendrites, and the connecting areas between axons and dendrites are called synapses. Each link enables neurons to transmit synapses that are represented by weights, receive data, and perform mathematical computations. Frank Rosenblatt, a psychologist, developed the first Artificial Neural Network (ANN) using this paradigm in 1958. Because they are composed of many nodes, ANNs are similar to neurons. The nodes are organized into multiple concealed layers and are securely connected. After being received by the input layer, the data is sequentially transferred via one or more hidden layers before being forecasted by the output layer.

More accurate predictions are produced as the neural network's function is improved over time by gradually changing the weights between neurons across a large number of input-output pairs. Therefore, if a lot of different cervical cancer photos are used to train the neural network, it will eventually be able to identify a cervical cancer in a new image. All machine learning models have the ability to generalize what they have learned from observed training data to unseen samples, which is their main advantage. As the input moves through each hidden layer, the weights and functions used in the nodes alter it until an output is produced. Learning occurs when the error propagates back to alter the weights when the generated output is compared to the actual value. This algorithm is known as the back propagation algorithm. For a set number of iterations (epochs) or until the error drops below the target level, the procedure is repeated.

Figure2. 2 Example of Artificial Neurons

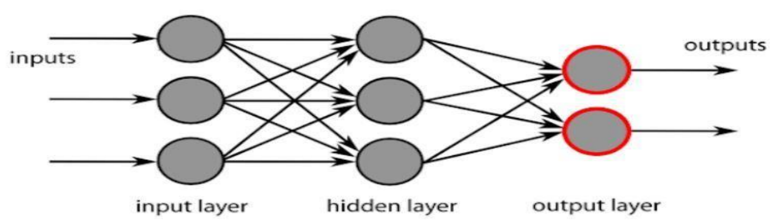


2.9 Feed forward neural network

An artificial neural network in which the connections between nodes do not create a loop is called a feed forward neural network. It is hence distinct from its progeny, recurrent neural networks. The earliest and most fundamental artificial neural network to be developed was the feed forward neural network. Information flows in this network solely in one direction, as seen in the input nodes to the output nodes via any hidden nodes that may exist. There are no loops or cycles in the network.

A type of multilayer neural network that is trained using the back propagation algorithm is called a feedforward neural network (also called a back propagation neural network, or BPNN). In order to minimize the network's error sum of squares through back propagation, it continuously modifies its weights and threshold using the gradient descent technique.

Figure 2.2 Feedforward neural network architecture



2.10 Multi-layer perceptron (MLP)

Multilayer perceptrons are one of the most important types of neural nets because many applications are successful implementations of MLPs. The architecture of the MLP is completely defined by an input layer, one or more hidden layers, and an output layer. Each layer consists of at least one neuron. The input vector is processed by the MLP in a forward direction, passing through each single layer

Deep Learning is a buzzword among researchers due to the increasing dependency on digital data. However, a simple Artificial Neural Network is only the solution to some problems as it is limited to a linear function and cannot handle complex and massive data. To help in this situation, a Multilayer perceptron Neural Network can work with non-linear functions.

2.11 Convolution Neural Network (CNN)

Popular deep learning neural network architecture in computer vision is the convolutional neural network (CNN). Computer vision is an area of artificial intelligence that allows a computer to comprehend and analyze visual information, such as images [29].

Artificial Neural Networks are very effective in machine learning. Text, audio, and image datasets are among the many datasets that use neural networks. Various kinds of neural networks are employed for various tasks; for instance, to forecast the word sequence we employ LSTMs, or recurrent neural networks; convolutional neural networks are used for image classification. We will construct a fundamental CNN building block in this blog.

2.12 Recurrent Neural Network (RNN)

The shortcomings of other artificial neural network (ANN) models can be addressed with the help of recurrent neural networks (RNN). Most of the ANN learned to make decisions based on context during training rather than recalling the steps from previous cases. In the meantime, RNN stores historical information and makes all of its decisions based on its prior knowledge.

When it comes to image classification, this approach works best. We might have to look to the future to make amends for the past. In this situation, bidirectional RNN is helpful for forecasting the future and learning from the past. For instance, we have handwritten samples in a number of inputs. If one of the inputs is ambiguous, we must check the other inputs again to discover the right context, which is based on a decision taken in the past. One of the earliest deep learning architectures that provide a roadmap for creating more deep learning algorithms is RNN. Natural language processing and speech recognition both frequently use it.

A unique kind of RNN called LSTM was created specifically to solve the issue of long-term dependencies by enabling the model to retain values over an arbitrary period of time. The two primary issues with RNN are exploding and vanishing gradients.

The disappearing gradient problem is a challenge that arises when back propagation and gradient-based learning techniques are used to train artificial neural networks. These techniques provide each neural network weight with an update proportional to the partial derivative of the error function over the current weight in each training cycle.

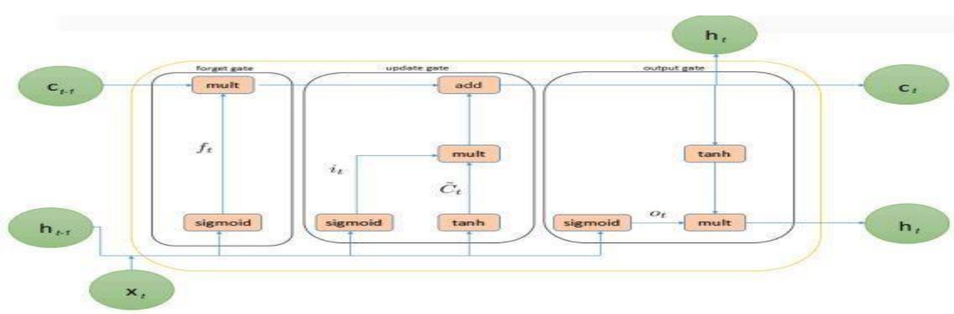
Although both LSTM and GRU are based on the standard RNN, they differ in their architectures and methods for getting around RNN's drawbacks, like short-term memory and vanishing or exploding gradients. With three gates (input, output, and forget) that regulate the flow of data into and out of the memory cell, LSTM has a more intricate structure than GRU. Gated recurrent units, or are simpler than second one and have two gates (reset and update) that control how the hidden state is updated. In many applications, both can produce results that are comparable, but depending on the task and data, they may have different benefits and drawbacks[38].
Although LSTM is more versatile and potent than overall, it is also more computationally costly and more prone to over fitting. GRU may have less memory and expressive capacity, but it is faster and more efficient.

$$i_t = \sigma(W_i . [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_i . [h_{t-1}, x_t] + b_i)$$

$$Ct=ftCt-it\tilde{C}\ t$$

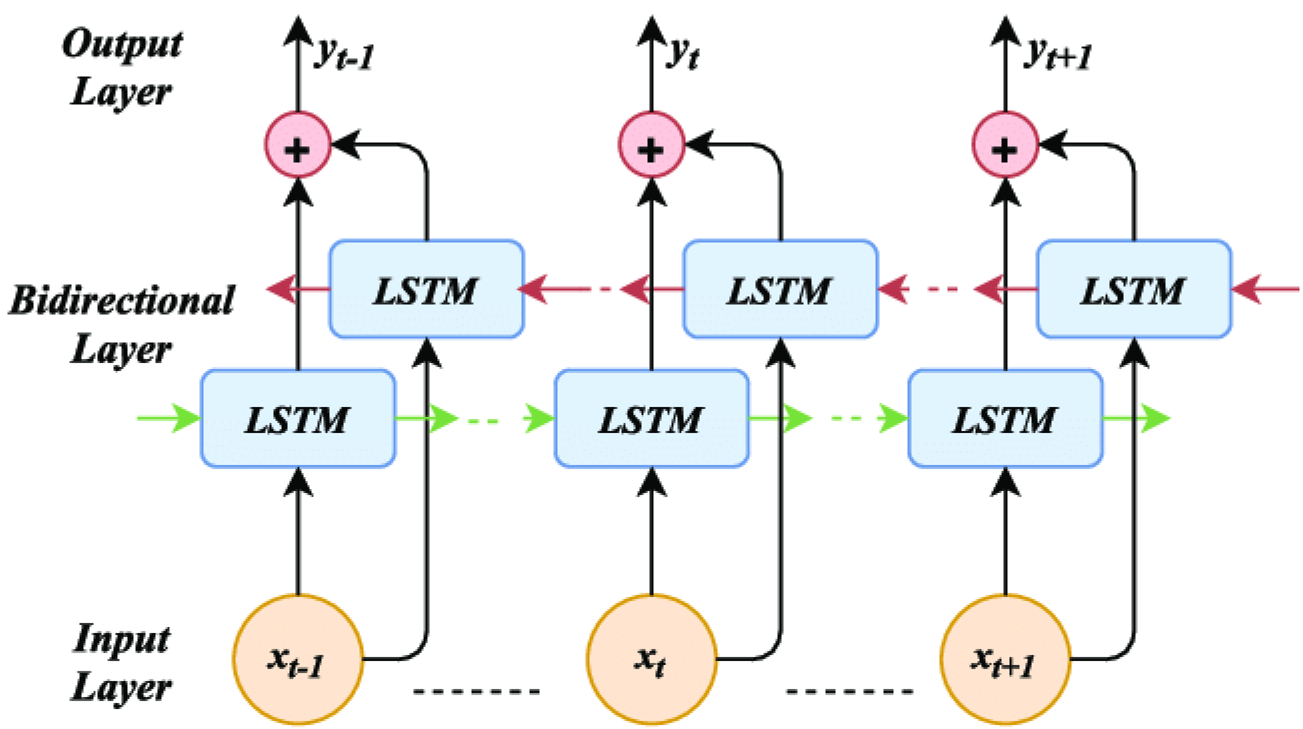
Figure2. 3 The internal structure of long short-term memory



Bidirectional-LSTM

Two-way LSTM Both past and future inputs can provide context information to bidirectional long short-term memory networks25. It can be difficult for RNN to incorporate long-term dependencies because portions of the gradient vector may exponentially grow or shrink over lengthy sequences [41]. The LSTM design uses a memory cell that can store a state for a long time, which solves the problem of learning long-term dependencies that the simple RNN presents. The Bidirectional-LSTM manipulates both past and future input by combining the forward hidden layer and the backward hidden layer. It is evident that Bi-LSTM is capable of learning in both directions and combining the information to generate a prediction. Using Keras, a BI-LSTM layer was added, and the embedded words served as input for the bidirectional LSTM model. In order to build bidirectional-LSTM and then fit the model to our data, TensorFlow's Keras has recently introduced a new bidirectional class[39].

Figure2.4 Bidirectional-LSTM[2]



Gated recurrent unit (GRU)

GRU uses gating units that influence the flow of information within the unit to address the vanishing gradient problem of a regular RNN. Large texts benefit greatly from GRU. GRU like LSTM has gating units that regulate data flow but unlike LSTM there is no need for additional designated memory cells [47]. The update and reset gates are two crucial gates of GRU that decide what information should be passed to the output27. The architecture depicted how GRU uses the two gates for output determination. The reset gate determines whether parts of the prior hidden state should be integrated with the present input to formulate a new hidden state. The update gate oversees deciding just how much of the prior hidden state should be kept and how much of the proposed new hidden state from the Reset gate should be included in the final hidden state. Whenever the Update gate is multiplied with the prior hidden state for the first time, the gate chooses which pieces of the prior hidden state to preserve in memory and dismiss the rest. As a result, whenever it utilizes the reverse of the Update gate to extract the newly proposed hidden state from the Reset gate, it is filling up the required pieces of information[14][32]

.

2.13 Related Works

Social media gives users a great opportunity to share and express their ideas, opinions, and thoughts about various events. People can now discuss, comment on, and critique a wide range of topics as well as write reviews and recommendations thanks to the proliferation of internet applications such as social networks, forums, and various microblogging. Numerous important details about goods, services, politics, events, and other topics are contained in these user-generated data[40].

Sentiment analysis is the study and comprehension of these social media users' opinions. The study of how people feel, think, and act toward things like goods, services, organizations, people, events, circumstances, and their characteristics is known as sentiment analysis. Sentiment analysis is the process of calculating and considering an individual's point of view as it is presented in a text to determine people's attitudes toward any subject, whether they are neutral, negative, or positive [44]. These days, social media platforms frequently publish multilingual posts, reviews, comments, and criticism data on a variety of subjects. But it can be difficult to evaluate posts and comments with multiple languages on specific subjects. Numerous studies have been conducted in an effort to address the data challenges associated with multilingual social media. Numerous studies pertaining to the ongoing research project are reviewed and categorized under this chapter according to the languages and methodologies they have employed[1].

The process of developing an automated opinion mining system from source data, including text, audio, and other kinds of data, is known as sentiment analysis. For creating automated sentiment classification models from user-generated data, especially on different social media datasets, there are numerous tools, approaches, and strategies available [50].

A thorough investigation based on natural language processing (NLP) has been conducted in this paper using simple neural networks (SNN), convolution neural networks (CNN), and long short-term memory (LSTM) neural networks[70]. A CNN layer is then added to the LSTM in another amalgamated model. The languages that were chosen were Bengali, Hindi, and English. Approximately 4,000 sample data points were gathered from social media sites like Twitter. A few movie review datasets from IMDB and Amazon were gathered and integrated with the Twitter dataset. Seventy-five percent of the total data collected was used for training, and the remaining twenty-five percent was used for testing. The authors employed both positive and negative sentiment classification polarity to categorize the sentiment polarity [55]. . From all the models the overall accuracy obtained was for the CNN+LSTM was the best and which score 84.1% accuracy[38].

2.13.1 Neural Network Based Sentimental Analysis

Conducted sentiment analysis on Amharic news and social media datasets using a deep learning approach [52]. They utilized word embedding's and employed CNN and LSTM models, achieving an accuracy of 86% with CNN and 84% with LSTM. In another study, analyzed sentiment in Amharic news articles comprising 3,000 entries. They adopted a hybrid approach using TF-IDF and word embedding's for feature extraction and applied CNN and SVM classifiers. Their results showed an accuracy of 85% for CNN and 80% for SVM. Further, explored sentiment analysis on Amharic social media texts, consisting of 5,000 comments, employing a deep learning approach [65]. They used text embeddings and experimented with LSTM and CNN models, reporting an accuracy of 82% for CNN and 80% for LSTM. Similarly, focused on Amharic news and social media datasets, performing sentiment analysis using word embedding with CNN and LSTM models. They achieved the same accuracy results as the previous study, with CNN reaching 86% and LSTM 84%.

Undertook a comparative study on sentiment analysis of Amharic and Oromo Twitter comments, involving 5,000 tweets. They utilized word embedding's for feature extraction and applied CNN and RNN classifiers. The study reported an accuracy of 85% for CNN and 82% for RNN, while for Oromo, CNN achieved 80%. In a bilingual sentiment analysis of Amharic and Afan Oromo movie reviews, employed cross-lingual word embeddings and used CNN and RNN models. Their results indicated an accuracy of 85% for LSTM on Amharic data and 83% for LSTM on Afan Oromo data. Lastly, conducted a study on Amharic news articles, encompassing 4,000 entries, utilizing a deep learning approach with Word2Vec embeddings. They employed LSTM and GRU classifiers and achieved accuracy rates of 84% for LSTM and 82% for GRU. These studies collectively demonstrate the effectiveness of various approaches and classifiers in sentiment analysis, highlighting the potential of deep learning models and hybrid approaches in achieving high accuracy across different datasets and languages[35].

Table2. 1 Comparative of Analysis Techniques on Sentiment Analysis

Authors	**Platforms and Dataset**	**Approach**	**Features**	**Classifiers**	**Results**
Asnakeh Abebe et al. (2019)	Amharic news and social media datasets	Deep learning Approach	Word Embeddings	CNN, LSTM	CNN=86%, LSTM=84%
Yohannes Getahun et al. (2020)	Amharic news articles(3,000 articles)	Hybrid approach	TF-IDF, word embeddings	CNN,SVM	CNN=85%, SVM=80%
Asnakeh Abebe et al. (2019)	Amharic social media texts (5,000 comments)	Deep learning approach	Text embeddings	LSTM, CNN	CNN=82%,LSTM=80%
Dereje Fekadu et al. (2020)	Amharic news and social media datasets	Sentiment Analysis	Word embeddings	CNN, LSTN	CNN=86%, LSTM=84%
Aklilu Tamiru et al. (2021)	Amharic and Oromo Twitter comments (5,000 tweets)	Comparative study	Word embeddings	CNN, RNN	accuracy: CNN=85%, RNN=82%, Oromo: CNN=80%

Rase, (2020)	Facebook (1,452 comments)	Deep Learning Approach	Word embeddings	LSTM and CNN	Accuracy of CNN= 89% & LSTM=87.6%
Bera et al, (2021)	Twitter (4,000 tweets)	Deep Learning Approach	Word embeddings	SNN CNN andLS TM	CNN+LST MAccurac y 84.1%
Fekadu Mesfin and Henok Gebre (2021)	Amharic and Afan Oromo movie reviews	Bilingual sentiment analysis	Cross-lingual word embeddings	CNN, RNN	Accuacy:A mhaic:LST M=85%,Af an Ormo: LSTM=83%
Kidanemariam Solomon et al.(2019)	Amharic news articles (4,000 articles)	Deep learning Approach	Word2Vec embeddings	LSTM, GRU	Accuracy: LSTM=84%, GRU=82% LSTM, GRU

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The design and execution of the suggested sentiment analysis model for ethio telecom Facebook and Twitter comments in Amharic and English are explained in this chapter. A wide range of research is being done on opinion mining and classifying comments from social media users into the proper categories. A number of techniques and processes are used in this study to distinguish between the polarities of user comments. The methods utilized to complete this thesis are described in this chapter, along with the model's implementation strategies, data gathering and preparation methods, software and hardware configuration methods, and evaluation approaches.

3.2 Proposed Models of Research Methodology

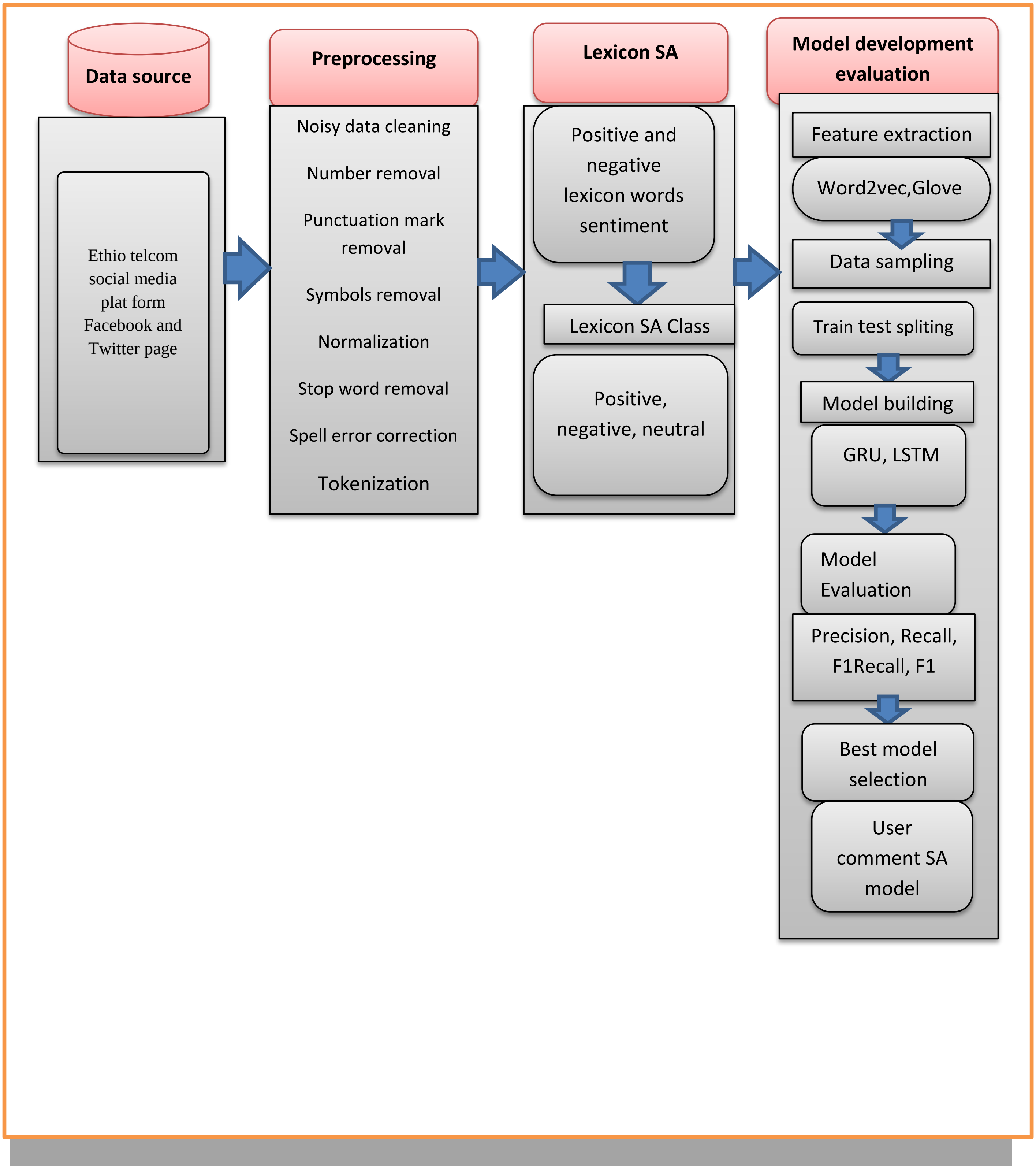
This research utilizes an experimental design for sentiment analysis of social media data acquired from Ethio telecom's Facebook and Twitter platforms. The general architecture of the proposed multilingual social media data sentiment analysis model is given in Figure 3.1 below. The next sections go into detail about the suggested sentiment analysis model's design and execution. Data collection, data pre-processing, lexicon-based sentiment analysis, feature extraction, data sampling, model building using deep learning classifiers, and evaluation of the developed models are the seven main components, which combine a variety of methods and techniques to accomplish the ultimate goal.

1. **Data Source**: The dataset was collected from Ethio telecom's Facebook and Twitter platforms. Some data were provided by the company Ethio telecom [70].
2. **Preprocessing & Cleaning Stage**: Various preprocessing and data cleaning techniques were applied to the dataset, such as removing noisy data, punctuation, symbols, numbers, and stop-words (from both languages). Additional preprocessing steps included character, word, and phrase normalization, sentence tokenization, lowercase conversion (only for English), and spell error correction [62].

3. **Deep Learning-Based Sentiment Analysis:** In this stage, sentiment score calculation was performed using advanced deep learning models. The datasets were categorized into three classes (positive, negative, and neutral) based on the sentiment scores generated by these models [68].
4. **Feature Extraction:** Deep learning models require numerical data. Feature extraction transforms raw text data into numerical features. Commonly used, the study employed advanced embedding techniques such as Word2Vec, GloVe, and BERT [48].
5. **Data Sampling (Data Splitting**): In deep learning, data splitting is usually done to prevent overfitting, which happens when a model fits its training data too well and doesn't generalize to new data. Common data splitting techniques include Train-Test splitting, and Cross-Validation was chosen for this study.
6. . **Model Building**: Following feature extraction, variety of deep learning architectures, such as RNN, LSTMs), and Gated (GRUs), were used to estimate sentiment. These models were chosen because they were able to capture both local and sequential patterns in the data.

7. Model Evaluation: The sentiment analysis task consists of multiple stages, including feature selection, polarity identification, data collecting, preprocessing, sentiment classification, and evaluation. The primary objective is to use several techniques to ascertain whether a language, text, or comment reflects a positive, negative, or neutral sentiment polarity. Sentiment evaluation criteria like accuracy, recall, precision, and F-measure were used to evaluate the performance of the constructed models.

Figure3.2 General Architecture of the Proposed Model



Python	A general-purpose programming language that is suitable for data preprocessing and machine learning algorithms implementation.
Google Colab	Short form of Google Colaboratory, is a free cloud-based platform provided by Google that allows users to write and execute Python code in a Jupyter notebook environment. It is particularly popular for machine learning, data analysis, and deep learning tasks due to its ease of use and access to powerful computing resources, including GPUs and TPUs
Anaconda Navigator	The Anaconda distribution comes with a desktop graphical user interface (GUI) that makes it simple to manage Conda packages and to launch environments, channels, and applications without the need for command-line commands.
Jupyter Notebook	We can create and share documents with equations, narrative text, live code, and visualizations using this open-source web application. Statistical modeling, data visualization, data transformation, data cleaning, and numerical simulation are among the applications.
TensorFlow	Google created the open-source deep learning framework TensorFlow. It offers extensive resources for creating and implementing machine learning models. TensorFlow Keras: Used for building and training neural networks with a high-level API. TensorFlow Hub: Accessed pre-trained models and embeddings for NLP tasks.
Keras	Keras It is a free and open-source distribution of the Python and R programming languages designed to make package management and deployment easier for applications pertaining to data science and deep learning. It comes with a number of code writing IDEs, such as Spyder and Jupyter Notebook. The coding notebook was used for implementation.

Scikit learn(sklearn)	Scikit-Learn is a machine learning library that provides tools for data preprocessing, model evaluation, and traditional ML algorithms. It was used for: Data Splitting: Divided data into training, validation, and test sets. Evaluation Metrics, Computed metrics like accuracy, precision, recall, and F1-score.
Pandas	High performance, easy to use data structures, and data analysis tools. We use it for data reading, manipulation, writing, and handling thedataset.
Numpy	Array processing for number, strings, and objects. We use it to handling our data set features for training and testing of the model
Matplotlib	Publication quality figures in python. We use it for data visualization.
Hugging Face Transformers	The Hugging Face Transformers library provides easy access to a wide range of pre-trained transformer models. These models are highly effective for NLP tasks such as sentiment analysis: -Pre-trained Models: Utilized models like BERT, GPT-2, and RoBERTa for sentiment analysis. - Fine-Tuning: Customized the pre-trained models to better suit the user comment dataset.
NLTK (Natural Language Toolkit)	NLTK is a comprehensive library for natural language processing in Python. It was used for basic text preprocessing tasks: Tokenization: Split text into words and sentences. Lemmatization and Stemming: Reduced words to their base forms.
Spacy	SpaCy is an advanced NLP library designed for performance and ease of use. It was used alongside NLTK for efficient text preprocessing: Named Entity Recognition, Identified entities in user comments. Dependency Parsing: Analyzed

	grammatical structure of sentences.
PyTorch	PyTorch is another leading deep learning framework, known for its dynamic computational graph and ease of use. It was used in conjunction with other libraries for building and training models: TorchText: Used for text processing and data handling. -Hugging Face Transformers: Integrated for leveraging state-of-the-art pre-trained models like BERT and RoBERTa.
Langdetect	Used for detecting the language of each word.
Hardware Tools	The main tools that are used with the selected software tools a very slow machine with CPU Intel(R) Core (TM) i5-7200U CPU @ 2.50GHz processor, memory 8 GB and 1 Tera byte was used.

3.4 Data Collection

The necessary data was collected via User Comments on Ethio telecom's Facebook and Twitter sites in both English and Amharic. The FDRE's official working language is Amharic, which facilitates communication among speakers of many languages throughout the nation. Ethio Telecom employs Amharic, the Ethiopian federal working language, as its working language and English for foreigners because it has a monopoly on all telecommunication services in Ethiopia. Customer reviews are generated in a variety of Ethiopian languages, including English, and Ethio Telecom publishes information about its goods, services, and products in both Amharic and English. English and Amharic, on the other hand, have more comments, which is why these two languages were selected for this bilingual sentiment analysis study. The table below provides a summary of the datasets used in this investigation.

Table3. 2 Dataset description

Data Descriptions			
Data Source	**Data Amount in Sentences (Comments)**	**Amount in Words**	**Labeled/ Class**
From Ethio Telecom company social media platforms (facebook and twitter)	13389	134813	Yes

3.4.1 Dataset Description and Characterization of the Collected Data

The aim of the study was to create a text-based classification system of Amharic-English (language-mixed) data. The information was gathered between May 2022 and January 2023 from two social media platforms: Facebook and Twitter of Ethiopian telecoms. Amharic and English-language comments on both platforms are included in the gathered dataset. 13,389 comments gathered from both social media networks make up the entire dataset. Facebook comments are the sole social media data used by the company for various purposes. Finding out what is being said about company brands, services and products, and general hot topics that are being brought up on social media and online platforms are the primary goals. In order to proactively address their issue, the company can use social media reviews as input and take them into consideration for future improvements. The goal of the Ethiopian Telecom social media review is to track customer feedback and comments/complaints, identify critical issues that impact customers' experiences, close communication gaps, and enhance brand images

As indicated on the below Figure 3.3 indicates that, there is no data cleansing and preprocessing. And also in sentiment categorization there are three classes namely; positive, negative and support classes, but for this research study there is no support classes. All support classes are re-reviewed by the researchers manually to positive, negative and neutral classifications.

Information about the dataset after it has been preprocessed.

Table3. 3 Total cleaned Dataset Description

Dataset Sources	Total Comments	Total Words	Minimum Length	Maximum Length	Mean Length
EthioTelecom (face book and twitter social media plat form)	13389	134813	1	210	10.07

3.4.2 Dataset Description of Language and Polarity Distribution

All datasets from both platforms are displayed in table 3.6 below, along with information on their distribution by language and target class. According to the table, out of 13,389 Facebook and Twitter comments, 52.91% (7084) are in Amharic, 28.75% (3850) are in English, and the rest 18.34% (2455) are in mixed languages.

Table3. 4 Total Dataset Descriptions of Language Distribution

Dataset Sources	No of Comments	Amharic Comments	English Comments	Mixed Comments	Manual Class
EthioTelecom (face book and twitter social media plat form)	138413	7084	3850	2455	With class

As shown in the below table 3.7, from total of 13,389 Facebook and Twitter comments, positive polarity comments are 48.31 % (6468), while negative polarity comments are 42.14% (5642), and the remaining of 9.55% (10304) are neutral comments

Table3. 5 Total Dataset Polarity Class Descriptions

Polarity Class	No of comments
Positive	6468
Negative	5642
Neutral	1279

Table3. 6 Sample of Dataset (Comments) in Languages

Type of Comments	**No of Comments**	**Sample Comments (Sentences)**
Pure Amharic comments	7084	**የማታ ጥቅል አገልግሎት ሰአቱ ቢሻሻል**
		ጥቅል አገልግሎት ለመሙላት ኔትወርኩ ያስቸግራል ይታሠብበት
Pure English Comments	3850	We need daily unlimited internet data!!
		Good job Keep your integrity!
		Poor quality network bale zones especially ginning surrounding
Mixed comments	2455	እናምስግናልን በጥም ጥሩ ነዉ.thank you
		telebirr internet free ቢሆን ጥሩ
		Wonderful. የተግባር ሰው ሆናቿል የ Wifi መቆራረጧን ናፍጥነት መቀነሷን ጉዳይም ኢልባት ብታገኝ
Total	**13,389**	

3.5 Data Preprocessing and Cleaning

The two terms used to prepare data for particular works are data preprocessing and data cleaning. It is the process of changing data from one form to another that is much more desired and useful, i.e., more informative and meaningful. By identifying and eliminating errors and inconsistencies, the data cleaning process enhances the quality of the data. Misspellings during data entry, missing values, or any other invalid data can lead to issues with data quality. The primary step in any deep learning model is cleaning and preprocessing social media data. Social media data is inherently noisy, multilingual, unstructured, and uncleaned. Enhancing the quality of retrieved social media data requires the use of prepossessing techniques. Preprocessing techniques are an essential part of all data analytical and natural language processing operations in order to reduce data complexity and improve data quality. In order to accomplish the study's goal, it is crucial to purify the dataset and eliminate any elements that are unnecessary or don't contribute significantly to sentiment analysis, such as stop words and any characters that could make it more difficult to analyze the data, like punctuation and special symbols. Several preprocessing techniques have been used to prepare the dataset, including the removal of stopwords, punctuation, various symbols, numbers, and noisy data (from both language datasets). Character, word, and phrase normalization, as well as spelling and grammar correction, are additional preprocessing steps.
Consequently, the following fundamental and significant data cleaning and preprocessing methods are applied to the gathered data.

3.5.1 Noisy Data Cleaning

The data is gathered from user comments on Facebook and Twitter. Numerous noisy elements are cleaned and eliminated from the dataset, such as multilingual words (apart from Amharic and English), irrelevant links, words and special symbols that have no meaning, single spellings, emojis, etc.

3.5.2 The Punctuation, Numbers and Special Symbols Removal

Punctuation symbols do not affect the sentiment analyses are removed from each and every sentences in the data. Symbols are [!"#$ %&\'()*+,-./:;<=>?@[\\]^_`{|} ~] etc.), are removed.

Especially Amharic language have the special punctuation mark like (“፤”, “፣”, “።”, etc.) are also included in the list of punctuation removal and removed from the datasets. In this study numbers (0-9) are not important and removed from the dataset.

In general, Punctuation, Numbers and Special Symbols are all removed as follows

1. Different symbols other than punctuation like [★ ❤✔□⊟`◇_]‹›« »= which founds in the collected dataset are removed.
2. Different common punctuation marks like [,“*^@#$&%.!”], including Amharic punctuation like [※። ፣ ፤ ፥ ፦ ፧ ፨] which found in the collected dataset are removed.
3. In the collected comment numbers [0-9], including Amharic numbers (geez numbers) like [፩ ፪ ፫ ፬ ፭ ፮ ፯ ፰ ፱ ፲ ፳ ፴] are removed.

4. All non-Amharic and non-English comments, emojis, unwanted space, irrelevant characters and symbols are removed.

Normalization of Characters and Word level

Text normalization is the process of converting a text into a standard form. Characters with the same pronunciation are known as homophones in the Amharic writing system but different symbols such as (ሀ፡ሐ፡ኀ፡ኸ), (ሰ፡ሠ), (ጸ፡ፀ), and (ዐ፡አ); for example, it is common to write አመሰግናለሁ and አመሠግናለሁ፣ interchangeably and also for word ፀሀይ (ጸሀይ, ጸሐይ, ጸኀይ, ፀሐይ) are used interchangeably. Amharic characters with 'ሀ' sound but different in structures like ['ኀ', 'ኁ', 'ኂ', 'ኃ', 'ኄ', 'ኅ', 'ኆ'], ['ሐ', 'ሑ', 'ሒ', 'ሓ', 'ሔ', 'ሕ', 'ሖ'] and ['ኸ', 'ኹ', 'ኺ', 'ኻ', 'ኼ', 'ኽ', 'ኾ'] are replaced by ['ሀ', 'ሁ', 'ሂ', 'ሀ', 'ሄ', 'ህ', 'ሆ'] respectively in comment dataset corpus.

Amharic characters with 'ሰ' sound but different in structures like ['ሠ', 'ሡ', 'ሢ', 'ሣ', 'ሤ', 'ሥ', 'ሦ'] are replaced by ['ሰ', 'ሱ', 'ሲ', 'ሳ', 'ሴ', 'ስ', 'ሶ'] respectively in comment dataset corpus..

Amharic characters with 'ፀ' sound but different in structures like ['ጸ', 'ጹ', 'ጺ', 'ጻ', 'ጼ', 'ጽ', 'ጾ'] are replaced to ['ፀ', 'ፁ', 'ፂ', 'ፃ', 'ፄ', 'ፅ', 'ፆ'] respectively in comment dataset corpus.

Amharic characters with 'አ' sound but different in structures like ['ዐ', 'ዑ', 'ዒ', 'ዓ', 'ዔ', 'ዕ', 'ዖ'] are replaced to ['አ', 'ኡ', 'ኢ', 'አ', 'ኤ', 'እ', 'ኦ'] respectively in comment dataset corpus.

Figure3. 2 Amharic character normalization

```
# Apply the punctuation, special characters, numbers, and emojis removal function
data['Comments'] = data['Comments'].apply(remove_punc_special_chars_and_emojis)

# Function for character level normalization
def normalize_char(token):
    replacements = {
        '[ኀሐኸ]': 'ሀ', '[ሑኁኹ]': 'ሁ', '[ኂሒኺ]': 'ሂ', '[ኃሓኻ]': 'ሃ', '[ኄሔኼዄ]': 'ሄ',
        '[ሕኅኽ]': 'ህ', '[ኆሖኾ]': 'ሆ', '[ሠ]': 'ሰ', '[ሡ]': 'ሱ', '[ሢ]': 'ሲ',
        '[ሣ]': 'ሳ', '[ሤ]': 'ሴ', '[ሥ]': 'ስ', '[ሦ]': 'ሶ', '[ዐ]': 'አ',
        '[ዑ]': 'ኡ', '[ዒ]': 'ኢ', '[ዓ]': 'አ', '[ዔ]': 'ኤ', '[ዕ]': 'እ',
        '[ዖ]': 'ኦ', '[ጸ]': 'ፀ', '[ጹ]': 'ፁ', '[ጺ]': 'ፂ', '[ጻ]': 'ፃ',
        '[ጼ]': 'ፄ', '[ጽ]': 'ፅ', '[ጾ]': 'ፆ', '[ቊ]': 'ቁ', '[ኵ]': 'ኩ',
        '[ዃ]': 'ኋ', '(ቱ[ዋአ])': 'ቷ', '(ሩ[ዋአ])': 'ሯ', '(ሱ[ዋአ])': 'ሷ',
        '(ሹ[ዋአ])': 'ሿ', '(ቁ[ዋአ])': 'ቋ', '(ቡ[ዋአ])': 'ቧ', '(ቹ[ዋአ])': 'ቿ',
        '(ሁ[ዋአ])': 'ኋ', '(ኑ[ዋአ])': 'ኗ', '(ኙ[ዋአ])': 'ኟ', '(ኩ[ዋአ])': 'ኳ',
        '(ዙ[ዋአ])': 'ዟ', '(ጉ[ዋአ])': 'ጓ', '(ደ[ዋአ])': 'ዷ', '(ጡ[ዋአ])': 'ጧ',
        '(ጩ[ዋአ])': 'ጯ', '(ጹ[ዋአ])': 'ጿ', '(ፉ[ዋአ])': 'ፏ', '(ሉ[ዋአ])': 'ሏ',
        '(ሙ[ዋአ])': 'ሟ'
    }

    for pattern, replacement in replacements.items():
        token = re.sub(pattern, replacement, token)

    return token

# Apply the character normalization function
data['Comments'] = data['Comments'].apply(normalize_char)
```

Repeated Characters Normalization: On social media, users occasionally use language that is unexpected. Users typically write things like "baaaaaad" in place of "bad," "happppppy" in place of "happy," "verrrrry costllllly" in place of "very costly" in English, and "ዊዊዊዊዉዉዉ“" in place of "ዊዉ“" in Amharic. All of these complexities are normalized to their original words.

Normalization aims to ensure uniform data standardization by transforming all the data in a consistent way.

Figure3.2 Repeated character normalization:

```python
# Function to replace repeated characters (e.g., hapyyyyyyyyyyy to happy)
def normalize_repeated_chars(word):
    return re.sub(r'(.)\1+', r'\1', word)
```

Replacing the contraction words: Common informal writing techniques for English comments include "isn't," "won't," "shouldn't," "10Q," and "tnx." These styles are prevalent, particularly on social media, and need to be adapted to the formal style of writing. Construction, acronyms, or abbreviations are terms used to describe this kind of informal writing style. Informally written language is frequently used on social media, particularly in tweets. However, these contraction words are not processed directly in the NLP experiment; instead, proper or formal words must be used in place of contraction, acronym, or abbreviation words.

Contraction words like „isn"t", „won"t", „shouldn't", „10Q" and „tnx" are normalized to „is not",„will not", „should not", „thank you" and „thanks" respectively

3.5.4 Stop-word Removal

Stop words are words that are eliminated from the dataset because they don't hold, don't add significant meaning to the sentiment analysis, or don't add extra information. The stop-words used in this study are prepared in both English and Amharic. Eliminating stop words improves processing efficiency and lowers memory and processing utilization. Additionally, stop words don't provide any context for sentiment classification in the sentence. From the gathered dataset and earlier related works, a total of 130 stop-words were prepared for Amharic and 180 for English. Yordanos (2021) collected about 54 stop-words that are suitable for this study and used them in Amharic sentiment analysis. The gathered dataset is cleared of stop-words in English (such as is, was, are, a, the, i, for, to, on, from, am, etc.) and Amharic (such as ነው፣ ሆነ፣ ወደ፣ ናቸው፣ ነበር፣ ብቻ፣ እሷ፣ እሷ፣ እሱ፣ እነርሱ, etc.

Figure3. 3 Stop word removal

```
#stopword list uploading
stopwords = pd.read_excel('stopwords.xlsx', header=None)
stopwords = stopwords[0].to_list()

#applying stopword removal on dataset
data['Comments'] =data['Comments'].apply(lambda x: ' '.join([word for word in x.split()
                                                              if word not in (stopwords)]))
```

3.2.1 Tokenization

Tokenizing raw dataset involves dividing into tiny units known as n-grams of tokens. These tokens may be characters, words, or subwords. Tokens can be distinguished from one another using quotation marks and commas or white space characters. The n-grams can be either uni-grams, which split the word into one word, bi-grams, which split the word into two words, or tri-grams, which split the word into three words. 134813 tokens or words were obtained in this study's experiments.

3.5.6 Other Preprocessing and Cleaning

Addition to the above dataset preprocessing and cleaning, converting all the words into lower case (for English comments), replacing multiple white spaces with single white space, and also manual cleaning such as emoji, non-English and non-Amharic comments are all removed. In this stage of lowercase conversion, Amharic language characters didn't have upper and lower case, but in this case lower casing are used for English language characters.

3.5.7 Negation Word Handling

Certain words are referred to as negation words because they alter the meaning of a sentence. Negative words include never, not, do not, no, and are. Some negative words, like "nor," "not," "no," and so on, are included in the list of stop words, particularly in the English language. However, because they have an impact on the sentiment classification, these words are not included in the lists of stop words because they have the ability to turn positive sentiment into negative sentiment, and they are handled appropriately.

3.6 Word Representation

Text feature extraction is still an important step in the deep learning for sentiment analysis. Building the model requires converting the preprocessed text dataset into a vector format because models cannot directly interpret raw text. Several word representation techniques must be used to numerically represent the tokens that are produced by text preprocessing. GloVe, FastText, and other tools were used for this deep learning project.

3.7 Model Development

The research objective is preprocessed datasets and deep learning techniques to create a sentiment analysis model for user comments.. they are good at processing sequential data and capturing context in text, deep learning models like Recurrent Neural Networks (RNNs) and Gated Recurrent Units (GRUs) are used. Learning context and long-term dependencies within sequences is a skill that RNNs and GRUs excel at.

3.8 Model Evaluation

Evaluating the effectiveness of the deep learning models that have been developed is the last phase of this study. A number of metrics, most notably Accuracy, Recall, Precision, and F1-score, are used to assess the suggested models. A Confusion Matrix, which compiles the model's accurate and inaccurate predictions, is used to calculate these evaluation metrics.

Confusion Matrix: is a tool that outlines the performance of the model by comparing the actual values to the predicted values. It provides the following results:

Table3. 7 Confusion Matrix

	Predicted Negative	**Predicted Positive**
Actual Negative	True Negative (TN)	False Positive (FP)
Actual Positive	False Negative (FN)	True Positive (TP)

Accuracy is the degree to which a measurement resembles true values or the appropriate values for that measurement. It is the frequency with which the classifier predicts a correction. It calculates the proportion of accurate forecasts to all occurrences.

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

Equation3. 1 :Accuracy

Precision: Determines the amount of accurately forecasted positive observations to all of the initial predictions. Out of all the predicted patterns in a positive class, it calculates the proportion of correctly predicted positive patterns..

$$Precision = \frac{TP}{TP + FP}$$

Equation3. 2 :precision

Recall: Answers to the question "how many of the true positives were recalled (found)" are recalled. In other words, the model's measure accurately identifies true positives by measuring the percentage of positive patterns that are correctly classified.

$$Recall = \frac{TP}{TP + FN}$$

Equation3. 3: Recall

F-measure/F1-score. It offers a method for creating a single metric that balances the precision and recall characteristics into a single figure.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Equation3. 4 F1 score

By utilizing these evaluation metrics, the effectiveness of the deep learning models for user comment sentiment analysis can be comprehensively assessed.

CHAPTER FOUR

EXPERMENTS, RESULTS AND EVALUATION

4.1 Implementation of the Proposed Solution

The main elements and suggested deep learning model for bilingual sentiment analysis which includes comments in Amharic, English, and mixed languages are covered. Data sampling ways feature extraction, deep learning sentiment analysis, and model evaluation experiments make up the proposed model.

1. **Data Sampling**: To make sure the data is appropriate for deep learning models, it is gathered and preprocessed. This entails separating the data into training and test sets, handling missing values, and normalizing text.

2. Feature Extraction: Text is transformed into numerical vectors that deep learning models can process using a variety of word representation techniques, including Word2Vec, GloVe, and FastText.

3. **Deep Learning Sentiment Analysis:** RNNs, LSTMs, and GRUs are among the deep learning models used in the sentiment analysis. To categorize user comments into distinct sentiment categories, these models are trained using the bilingual dataset that has already been preprocessed.

```
# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)
```

4. Model Evaluation Experiments: We use metrics like Accuracy, Precision, Recall, and F1-score to assess each deep learning model's performance. These metrics offer a thorough evaluation of how well the models classify sentiments.

Sample GRU algorithm code

Bidirctional GRU modle

```
#Load the data

df = pd.read_excel('all_facebook_and_twitter_dataset.xlsx')

# Define the model using the Sequential API

model = Sequential([

Input(shape=input_shape),  # Input layer

Embedding(input_dim=max_features, output_dim=256),  # Increased embedding
size

Bidirectional(GRU(128, return_sequences=True)),  # Bidirectional GRU for
context from both directions

BatchNormalization(),  # Batch normalization for better convergence

Dropout(0.5),

GlobalAveragePooling1D(),  # Pooling to reduce dimensionality

Dense(64, activation='relu'),  # Additional dense layer

Dropout(0.5),  # Dropout to prevent overfitting

Dense(3, activation='softmax')  # Output layer
```

4.2 Tools and Implementation Environment

The following specifications are used to develop and test the bilingual sentiment analysis **Operating System**: Windows 10 Home

Processor: Processor Intel(R) Core(TM) i5-7200U CPU @ 2.50GHz, 2712 Mhz, 2 Core(s), 4 Logical Processor(s)

Memory: 8.0GB RAM

Storage: 1000GB HDD

Development Tools:

Python: The Python programming language (Jupyter Notebook version 3.9) is used for all stages of development, from data preprocessing to model training and evaluation.

Anaconda Navigator: This tool is used to manage the Python environment and packages.

TensorFlow and Keras: These libraries are utilized for building and training the deep learning models.

Microsoft Excel: Excel is used for data organization and conversion to UTF-8 encoding.

Steps for Implementation:

Data Preprocessing: The dataset is cleaned and preprocessed using Python. This entails changing the text to lower case, eliminating stop words, and tokenizing.

Feature Extraction: Text is transformed into numerical vectors using word representation techniques like Word2Vec, GloVe, and FastText.

Model Training: TensorFlow and Keras libraries are used to build and train deep learning models (RNN,LSTM,andGRU).

Model Evaluation: Accuracy, precision, recall, and F1-score metrics are used to assess the trained models. The classification performance is analyzed using confusion matrices. The suggested bilingual sentiment analysis solution is successfully implemented and tested by employing these tools and methodologies, guaranteeing reliable performance and precise sentiment classification.

4.3 Data Sampling Methods in Deep Learning

Setting some data for training and testing is essential before beginning any deep learning model. Cross-validation and train-test data split are the two most popular and well-known data sampling techniques in deep learning. Train-test data split, sometimes referred to as random sampling, is chosen for this investigation.

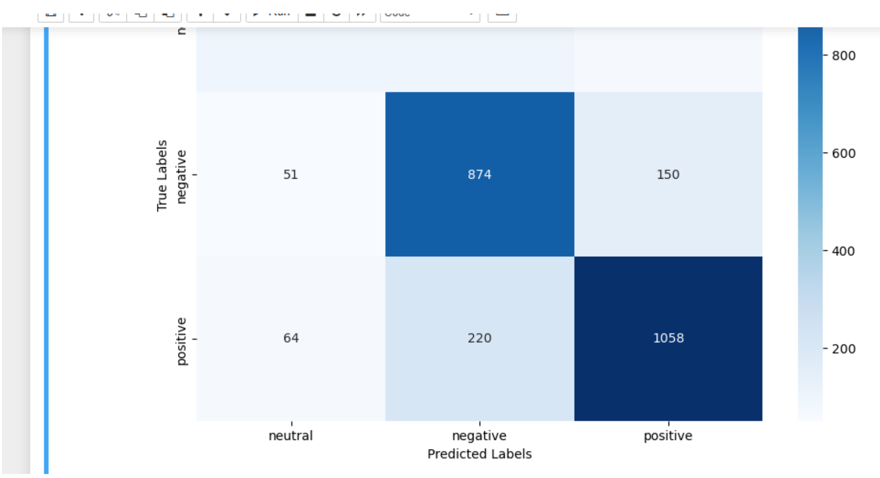
Splitting Train-Test: The simplest method in deep learning is to divide the dataset into training and test datasets. After training on the training dataset, the model will assess its performance on unseen data using the test dataset. The model learns from the training dataset's known outputs in order to subsequently generalize to other data. The predictions made by the trained model are tested using the test dataset (or subset). Train-test splitting, as implemented with Anaconda Navigator and Python, entails dividing the data into training and testing sets at random in a predetermined ratio. Experiments were conducted in this study using ratios of 8:2, and the results showed the best performance.

```
# Function to train and evaluate the model with train-test splits

# Train-test split

X_train, X_test, y_train, y_test = train_test_split(padded_sequences, labels, test_size=0.2, random_state=42)
```

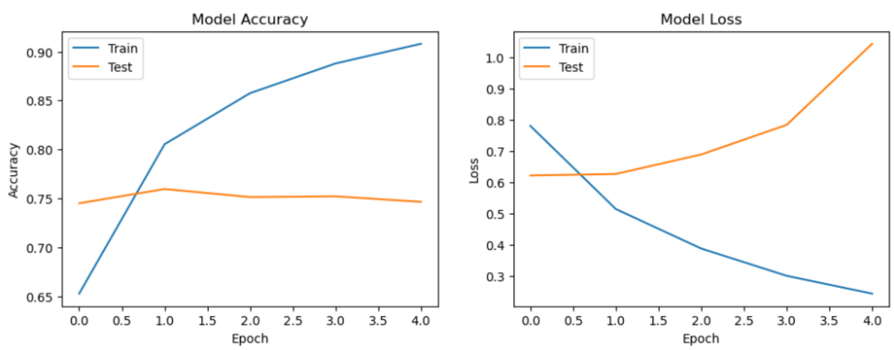
Table 4.1 Train-Test *Experiments results*

Train-Test (by 80%/20% train/test splitting)				
Models	**AC**	**F1**	**Precision**	**Recall**
LSTM	0.7438	0.7412	0.7392	0.7438
GRU	0.7367	0.7067	0.7264	0.7367

Confusion matrix



Accuracy and loss graph



4.4 Feature Extractions Experiment

The most crucial stage in deep learning text classification is converting text into a numerical representation, commonly referred to as a vector. Tokenization, stop-word removal, data cleaning, and other text preprocessing techniques are inputs for feature extraction. An embedding layer is frequently used in deep learning to extract features. As the model is being trained, the Embedding layer transforms text sentences into dense numeric vectors. An embedding layer was used in this study to extract features. In order to identify the optimal model configuration, 13,389 Facebook and Twitter comments were used to train and assess the deep learning model. The model's performance was assessed in the feature extraction experiments using train-test split ratios of 80%/20%. Tokenization was used in the Python code to transform the text into integer sequences, which were then padded to guarantee consistent length. To learn the dense vector representations of words during training, these sequences are run through an embedding layer in RNN, GRU, and LSTM architecture. To identify the optimal performance ratio, models are assessed using accuracy, precision, recall, and F1-score.

4.5 Deep Learning Classification Experiments

The goal of experimental is to determine which of two deep learning architectures GRU and LSTM is best suited for sentiment analysis of mixed-language social media data in Amharic and English. The experiments have been conducted using the deep learning frameworks TensorFlow and Keras. While Keras is a high-level neural networks API written in Python that can be used with TensorFlow, TensorFlow is an open-source machine learning library. The classifiers are implemented using Keras to create a deep learning model. In deep learning, classification is a predictive modeling task that entails. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are the deep learning architectures chosen for this investigation. Keras is used to implement all models with a TensorFlow backend. To answer the research questions of this study, a variety of experiments are carried out. Various text preprocessing methods are used to eliminate useless and false words prior to comparing the classifier architectures. The chosen deep learning architectures are then used in the experiments with the preprocessed text. Alongside the chosen deep learning models, word embeddings like Word2Vec or GloVe are used for feature extraction. A total of 13,389 Facebook and Twitter comments are used as the dataset for the experiments.

4.6 Discussion of Experimental Results

Two deep learning algorithms were used in the experiments, as shown in the results in Table 4.1 above. These experiments were conducted on a dataset consisting of 13,389 comments collected from Twitter and Facebook. The objective was to evaluate the performance of the LSTM and

GRU models using Train-Test Splitting techniques. For the Train-Test Splitting experiments, an 80%/20% split was employed. The LSTM model achieved an accuracy of 0.7438, a precision of 0.7392, a recall of 0.7438, and an F1-score of 0.7412 for the 80%/20% split. In contrast, the GRU model obtained an accuracy of 0.7367, a precision of 0.7264, and a recall of 0.7067 for the same split. These results indicate a noticeable improvement in the performance of the LSTM model compared to the GRU model.

Comparative Analysis:

The LSTM model performed better overall than the GRU model in Train-Test Splitting. Its best results came with an 80%/20% split, achieving an F1-score of 0.7412, accuracy of 0.7438, precision of 0.7392, and recall of 0.7438. Although the GRU model performed well in the 80%/20% split, the LSTM model is more consistent and reliable, making it the better choice.

Conclusion, According to the experimental results, the LSTM model with a train-test split is the most effective and reliable for analyzing the sentiment of the collected social media comments. This approach is recommended for this research as it ensures consistent and generalizable results.So Ethio Telecom use deep learning LSTM model for aspect based sentiment analysis integrate Facebook and Twitter social media plat forms automatically generate comments and predict customer opinions is it positive, negative or neutral.

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CHAPTER FIVE

CONCLUSION AND FUTURE WORKS

5.1 Introduction

The thesis concludes in this chapter, which also discusses the study's weaknesses and makes suggestions for additional research.

5.2 Conclusion

This study used deep learning techniques to analyze comments from Ethio Telecom's Facebook and Twitter social media pages using Aspect-Based Sentiment Analysis (ABSA). Targeting particular elements like service quality, pricing, network performance, and customer support, the study sought to examine customer sentiments at a fine level. The following are the main conclusions and contributions of this work:

1. **Dataset Development**:

In order to overcome the lack of resources for Amharic text analysis, a labeled dataset of Amharic and English comments was produced. Deep learning models were trained and assessed using this dataset as a basis.

2. **Model Implementation**:

Modern deep learning architectures were used, including Transformers, Bidirectional LSTM (BiLSTM), and attention mechanisms. These models performed well in identifying contextual and semantic subtleties in comments written in both English and Amharic.

3. **Performance Evaluation:**

The models' ability to extract and analyze aspect-based sentiments was demonstrated by their competitive accuracy and F1-scores in both language settings. Preprocessing methods unique to

Amharic, like stop word removal and normalization, were essential for enhancing model performance.

4. **Practical Implications**:

Ethio Telecom can better understand customer feedback and proactively address specific issues with the help of the research's findings. The results also highlight ABSA's potential to improve marketing and customer service decision-making.

Social networking sites now link people all over the world and enable multilingual idea and thought sharing. Large volumes of multilingual social media data have resulted from this, which is particularly advantageous for commercial entities such as Ethio Telecom. Nevertheless, social media multilingual data is frequently unstructured, mixed-language, containing spelling mistakes and variants, and containing grammatically varied and condensed content. It is challenging to use efficiently because of these features.

Generally, social media data is noisy and unstructured, containing a variety of languages, spelling and grammar variations, abbreviations, and common online jargon. Because the languages involved have different properties, preprocessing such data is difficult. This study suggested a methodological strategy for applying a variety of computational techniques to the analysis of mixed-language social media data. The primary contribution is offering a technique to assist corporate entities in more effectively and meaningfully analyzing noisy, unstructured, mixed-language social media data for sentiment analysis.

5.3 Recommendations and Future Work

Developing a sentiment analysis model for bilingual social media data was the main goal of this study. A number of issues must be resolved in order to enhance the model, particularly in lexicon sentiment analysis:

Recommendations

Data Collection and Labeling: To increase the robustness of the model, enlarge the dataset to include more interactions and comments from different social media platforms. **Improvements to Preprocessing**: Create increasingly complex preprocessing strategies, such as advanced tokenization techniques and language detection algorithms, which are better equipped to manage the particular difficulties presented by mixed-language text. To cut down on data noise, incorporate grammar and spell-checking tools those are specific to both Amharic and English.

Sentiment Lexicons: Develop and apply sentiment lexicons tailored to Amharic to improve the accuracy of lexicon-based sentiment analysis. Update the sentiment lexicons frequently to take into account changing social media language usage.

Future works:

While this study provides valuable insights, several areas remain open for future exploration:

1. **Multilingual and Code-Switched Analysis**:

Expand the study to incorporate multilingual pre-trained models like mBERT or XLM-Roberta to handle code-switched comments, which are prevalent on Ethiopian social media platforms.

2. **Real-Time Analysis**:

Create a real-time sentiment analysis pipeline to give Ethio Telecom's customer support staff instant insights so they can address customer concerns quickly.

3. **Aspect Extraction Automation**:

Reduce the need for manually labeled data by implementing automated aspect extraction using unsupervised or semi-supervised approaches.

4. **Integration with Business Intelligence Tools**:

For smooth operational advantages, incorporate sentiment analysis findings with Ethio Telecom's decision-support and customer relationship management (CRM) platforms.

By addressing these areas, future research can further refine ABSA techniques and contribute to a deeper understanding of customer sentiments in multilingual and under-resourced settings.

Reference

[1] F. Alemayehu, M. Meshesha, and J. Abate, "Amharic political sentiment analysis using deep learning approaches," *Sci. Rep.*, vol. 13, no. 1, pp. 1–15, 2023, doi: 10.1038/s41598-023-45137-9.

[2] P. M. Nadkarni, L. Ohno-Machado, and W. W. Chapman, "Natural language processing: n introduction," *J. Am. Med. Informatics Assoc.*, vol. 18, no. 5, pp. 544–551, Sep. 2011, doi: 10.1136/AMIAJNL-2011-000464/3/M_AMIAJNL-2011-000464FIG1.JPEG.

[3] "Search | Mendeley", Accessed: Jan. 17, 2025. [Online]. Available: https://www.mendeley.com/search/

[4] H. Li, X. Cheng, K. Adson, T. Kirshboim, and F. Xu, "Annotating Opinions in German Political News".

[5] T. Tesfa, B. Belete, S. Abera, S. K. Mohapatra, and T. K. Das, "Aspect-Based Sentiment Analysis on Amharic Text for Evaluating Ethio-Telecom Services," *2nd Int. Conf. Emerg. Trends Inf. Technol. Eng. ic-ETITE 2024*, 2024, doi: 10.1109/IC-ETITE58242.2024.10493748.

[6] O. Appel, F. Chiclana, J. Carter, and H. Fujita, "A hybrid approach to sentiment analysis," *2016 IEEE Congr. Evol. Comput. CEC 2016*, pp. 4950–4957, Nov. 2016, doi: 10.1109/CEC.2016.7744425.

[7] J. Khairnar and M. Kinikar, "Machine Learning Algorithms for Opinion Mining and Sentiment Classification," *Int. J. Sci. Res. Publ.*, vol. 3, no. 6, 2013, Accessed: Jan. 17, 2025. [Online]. Available: www.ijsrp.org

[8] N. Farra, E. Challita, R. A. Assi, and H. Hajj, "Sentence-level and document-level sentiment mining for arabic texts," *Proc. - IEEE Int. Conf. Data Mining, ICDM*, pp. 1114–1119, 2010, doi: 10.1109/ICDMW.2010.95.

[9] J. Cleland-Huang, A. Czauderna, M. Gibiec, and J. Emenecker, "A machine learning approach for tracing regulatory codes to product specific requirements," *Proc. - Int. Conf. Softw. Eng.*, vol. 1, pp. 155–164, 2010, doi: 10.1145/1806799.1806825.

[10] R. Ahmad, Y. Shaikh, and S. Tanwani, "Aspect Based Sentiment Analysis and Opinion Mining on Twitter Data Set Using Linguistic Rules," *Indian J. Sci. Technol.*, vol. 16, no. 10, pp. 764–774, 2023, doi: 10.17485/IJST/v16i10.2138.

[11] N. Godbole, M. Srinivasaiah, and S. Skiena, "Large-Scale Sentiment Analysis for News and Blogs", Accessed: Jan. 17, 2025. [Online]. Available: http://www.textmap.com/sentiment.

[12] C. T. C PG Scholar and S. Joseph Asst Professor, "Aspect based Opinion Mining from Restaurant Reviews," *Int. J. Comput. Appl.*, pp. 975–8887.

[13] A. D. ' Andrea, F. Ferri, and P. Grifoni, "Approaches, Tools and Applications for Sentiment Analysis Implementation," *Int. J. Comput. Appl.*, vol. 125, no. 3, pp. 975–8887, 2015, Accessed: Jan. 17, 2025. [Online]. Available:

http://messenger.yahoo.com/features/emoticons

[14] N. Azmina, M. Zamani, S. Z. Z. Abidin, N. Omar, and M. Z. Z. Abiden, "Sentiment Analysis: Determining People's Emotions in Facebook".

[15] M. Godsay, "The Process of Sentiment Analysis: A Study," *Int. J. Comput. Appl.*, vol. 126, no. 7, pp. 975–8887, 2015, Accessed: Jan. 17, 2025. [Online]. Available: http://www.cs.uic.edu/~liub/fbs/sentiment-analysis.html

[16] C. Lei *et al.*, "A comparison of random forest and support vector machine approaches to predict coal spontaneous combustion in gob," *Fuel*, vol. 239, pp. 297–311, Mar. 2019, doi: 10.1016/J.FUEL.2018.11.006.

[17] M. Yifiru Tachbelie aus Addis Ababa and I. Wolfgang Menzel, "Morphology-Based Language Modeling for Amharic," 2010, Accessed: Jan. 17, 2025. [Online]. Available: https://ediss.sub.uni-hamburg.de/handle/ediss/3816

[18] M. Kassa Gobena, "Implementing an open source amharic resource grammar in GF," 2011. Accessed: Jan. 17, 2025. [Online]. Available: https://hdl.handle.net/20.500.12380/146295

[19] R. P. Lebret, "Word Embeddings for Natural Language Processing," 2016, doi: 10.5075/EPFL-THESIS-7148.

[20] F. Menuta, "Over-differentiation in Amharic Orthography and Attitude towards Reform," *Ethiop. J. Soc. Sci. Lang. Stud.*, vol. 3, no. 1, pp. 3–32, Jun. 2016, Accessed: Jan. 17, 2025. [Online]. Available: https://journals.ju.edu.et/index.php/ejssls/article/view/732

[21] D. Singh Tomar Pankaj Sharma VITM and G. AsstProfessor, "A Text Polarity Analysis Using Sentiwordnet Based an Algorithm", Accessed: Jan. 17, 2025. [Online]. Available: www.ijcsit.com

[22] "Wondwossen Philemon and Wondwossen Mulugeta, "A Machine Learning Approach to Multi-Scale Sentiment Analysis of Amharic Online Posts " HiLCoE Journal of Computer Science and Technology, vol. Vol. 2, p. 8, 2015 - Google Search." Accessed: Jan. 17, 2025. [Online]. Available: https://www.google.com/search?q=Wondwossen+Philemon+and+Wondwossen+Mulugeta%252C+%2522A+Machine+Learning+Approach+to%250D%250AMulti-Scale+Sentiment+Analysis+of+Amharic+Online+Posts+%2522+HiLCoE+Journal+of+Computer%250D%250AScience+and+Technology%252C+vol.+Vol.+2%252C+p.+8%25

[23] B. Pang, "AUTOMATIC ANALYSIS OF DOCUMENT SENTIMENT," 2006.

[24] R. Sharma, S. Nigam, R. Jain, M. Tech Scholar, B. Vidyapith, and I. Rajasthan, "Mining of product reviews at aspect level," *Int. J. Found. Comput. Sci. Technol.*, vol. 4, no. 3, Jun. 2014, doi: 10.5121/ijfcst.2014.4308.

[25] D. A. Ostrowski, "A Proposed Novel Approach for Sentiment Analysis and Opinion Mining," *Proc. - 2010 IEEE 4th Int. Conf. Semant. Comput. ICSC 2010*, pp. 394–401, Apr. 2014, doi: 10.1109/ICSC.2010.29.

[26] T. T. Hailu, "OPINION MINING FROM AMHARIC BLOG," 2013.

[27] V. K. Mishra and H. Tiruwa, "Aspect-Based Sentiment Analysis of Online Product Reviews," *https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-*

5225-2031-3.ch010, pp. 175–191, Jan. 1AD, doi: 10.4018/978-1-5225-2031-3.CH010.

[28] I. Habernal and J. Eckle-Kohler, "Argumentation Mining on the Web from Information Seeking Perspective", Accessed: Jan. 17, 2025. [Online]. Available: www.ukp.tu-darmstadt.de

[29] K. Sarkar, "Sentiment polarity detection in Bengali tweets using deep convolutional neural networks," *J. Intell. Syst.*, vol. 28, no. 3, pp. 377–386, Jul. 2019, doi: 10.1515/JISYS-2017-0418/MACHINEREADABLECITATION/RIS.

[30] M. Khan and A. Srivastava, "A Review on Sentiment Analysis of Twitter Data Using Machine Learning Techniques," *Int. J. Eng. Manag. Res.*, vol. 14, no. 1, pp. 186–195, Feb. 2024, doi: 10.5281/ZENODO.10791471.

[31] O. Kucuktunc, B. B. Cambazoglu, I. Weber, and H. Ferhatosmanoglu, "A large-scale sentiment analysis for Yahoo! Answers," *WSDM 2012 - Proc. 5th ACM Int. Conf. Web Search Data Min.*, pp. 633–642, 2012, doi: 10.1145/2124295.2124371.

[32] G. Yoo and J. Nam, "A Hybrid Approach to Sentiment Analysis Enhanced by Sentiment Lexicons and Polarity Shifting Devices," pp. 21–28, May 2018, Accessed: Jan. 17, 2025. [Online]. Available: https://hal.science/hal-01795217

[33] H. Thakkar and D. Patel, "Approaches for Sentiment Analysis on Twitter: A State-of-Art study," Dec. 2015, Accessed: Jan. 17, 2025. [Online]. Available: https://arxiv.org/abs/1512.01043v1

[34] "Sentiment Analysis and Opinion Mining - Bing Liu - Google Books." Accessed: Jan. 17, 2025. [Online]. Available: https://books.google.com.et/books?hl=en&lr=&id=xYhyEAAAQBAJ&oi=fnd&pg=PP1&dq=Bing+Liu,+Sentiment+Analysis+and+Opinion+Mining:+Morgan+%26+Claypool+2012&ots=rlUBIEQ0Au&sig=hxc3rpccJupHGQZMubm5U6PP1eA&redir_esc=y#v=onepage&q=Bing Liu%2C Sentiment Analysis and Opinion Mining%3A Morgan %26 Claypool 2012&f=false

[35] S. Schrauwen, "MACHINE LEARNING APPROACHES TO SENTIMENT ANALYSIS USING THE DUTCH NETLOG CORPUS," 2010.

[36] S. Kasthuri, L. Jayasimman, and A. N. Jebaseeli, "An Opinion Mining and Sentiment Analysis Techniques: A Survey," *Int. Res. J. Eng. Technol.*, 2016, Accessed: Jan. 17, 2025. [Online]. Available: www.flipkart.com

[37] J. R. Casas and J. Neumann, "Context Awareness triggered by Multiple Perceptual Analyzers," *Emerg. Artif. Intell. Appl. Comput. Eng.*, pp. 371–383, 2007, Accessed: Jan. 17, 2025. [Online]. Available: https://books.google.com/books/about/Emerging_Artificial_Intelligence_Applica.html?id=vLiTXDHr_sYC

[38] S. Z. El Jko Ag I ´ C, D. Jel, M. Erk, and L. Er, "Rule-Based Sentiment Analysis in Narrow Domain: Detecting Sentiment in Daily Horoscopes Using Sentiscopě," pp. 115–124, 2012, Accessed: Jan. 17, 2025. [Online]. Available: http://lt.ffzg.hr/sentiscope/

[39] Maciej Serda *et al.*, "Synteza i aktywność biologiczna nowych analogów tiosemikarbazonowych chelatorów żelaza," *Uniw. śląski*, vol. 7, no. 1, pp. 343–354, 2013, doi: 10.2/JQUERY.MIN.JS.

[40] A. Analysis`oscar and R. Llombart, “Using machine learning techniques for sentiment analysis.” Accessed: Jan. 17, 2025. [Online]. Available: https://ddd.uab.cat/record/181585

[41] Sharma, D., Sabharwal, M., Goyal, V., & Vij, M. (2020). Sentiment analysis techniques for social media data: A review. In First International Conference on Sustainable Technologies for Computational Intelligence (pp. 75-90). Springer, Singapore..

[42] Kharde, V., & Sonawane, P. (2016). Sentiment analysis of twitter data: a survey of techniques. arXiv preprint arXiv:1601.06971..

[43] Zabha, N. I., Ayop, Z., Anawar, S., Hamid, E., & Abidin, Z. Z. (2019). Developing cross-lingual sentiment analysis of Malay Twitter data using lexicon-based approach. Int. J. Adv. Comput. Sci. Appl., 10(1), 346-351..

[44] Padmaja, S., & Fatima, S. S. (2013). Opinion mining and sentiment analysis-an assessment of peoples‟ belief: A survey. International Journal of Ad hoc, Sensor & Ubiquitous Computing, 4(1), 21-33. doi: 10.5121/ ijasuc.2013.4102.

[45] W. F. ,. ,. Arif, A. Saduf and I. K. Asif, Advances in Deep Learning, vol. 57, Springer .

[46] J. Schmidhuber, Deep Learining in neural networks: An overview, Neural Networks, vol. .

[47] J. Schmidhuber, Deep Learining in neural networks: An overview, Neural Networks, vol. .

[48] W. F. ,. ,. Arif, A. Saduf and I. K. Asif, Advances in Deep Learning, vol. 57, Springer .

[49] W. F. ,. ,. Arif, A. Saduf and I. K. Asif, Advances in Deep Learning, vol. 57, Springer .

[50] B. Y. a. C. A. D. L. M. p. 2. G. Ian.

[51] A. K. Jain, J. Mao and K. M. Mohiuddin, Artificial neural networks, A tutorial In: Computer .

[52] S. Sharma, "Activation Functions in Neural Networks," 6 9 2017. [Online]. Available: .

[53] S. Mahanama, "Introduction to Artificial Neural Networks(ANN)," Analytics Vidhya, 10 .

[54] Brilliant, "Feedforward neural network," 2018..

[55] A. Zell, Simulation Neuronaler Netze [Simulation of Neural Networks], 1 ed., German: .

[56] J. Schmidhuber, Deep Learining in neural networks: An overview, Neural Networks, vol. .

[57] A. Zell, Simulation Neuronaler Netze [Simulation of Neural Networks], 1 ed., German: .

[58] U. Karn, "A Quick Introduction to Neural Networks," 2016. .

[59] A. K. Jain, J. Mao and K. M. Mohiuddin, Artificial neural networks, A tutorial In: Computer .

[60] W. F. ,. ,. Arif, A. Saduf and I. K. Asif, Advances in Deep Learning, vol. 57, Springer .

[61] M. Valueva, N. Nagornov, P. Lyakhov, G. Valuev and N. Chervyakov, Application of the .

[62] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley and S. C. Ozair, .

[63] C. Aggarwal, Neural Networks and Deep Learning, Switzerland AG: Springer International .

[64] C. Szegedy, S. Ioffe, V. Vanhoucke and A. Alemi, "Inception-v4, Inception-ResNet and the Impact of Residual Connection on Learning," in AAI Conference, 2017..

[65] A. Graves, G. Hinton and A. Mohamed, "Speech recognition with deep recurrent neural networks," in IEEE international conference on acoustics, speech and signal processing, 2013..

[66] F. A. Gers, J. Schmidhuber and F. Cummins, Learning to forget: Continual prediction with LSTM, 1999..

[67] Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), e1253..

[68] Rase, M. O. (2020). Sentiment Analysis of Afaan Oromoo Facebook Media Using Deep Learning Approach. New Media Mass Commun, 90, 7..

[69] Bera, A., Ghose, M. K., & Pal, D. K. (2021). Sentiment Analysis of Multilingual Tweets Based on Natural Language Processing (NLP). International Journal of System Dynamics Applications (IJSDA), 10(4), 1-12..

[70] Asnakech Abebe, A., et al. (2019). Sentiment analysis using deep learning on Amharic news and social media datasets. [Journal/Conference], [Volume(Issue)], pages. [Publisher/Institution]..

Appendix I: Sample of Dataset

	Comments	M-Class
2	እባካችሁ አለታዊ ፖኬጅ ላይም ማሻሻያ አድርጉ ለእኛ ለድሆቹም አስቡ እንጂ	positive
3	መቼነው ቅናሹ የሚጀምረው wifi የመኖሪያባለ mg ባለ mg የነበረው ስንት ሚቀንሰውስ	positive
4	የቴሌን የተወሰነ ለግሉ ዘርፍ ይሸጣል የተባለው የት ደረሰ ሀገራቱ ተፎካካሪ የሆነ ሌላ አማራጭ ኔትወርክ ከሌላ መቼም (	negative
5	safaricom እንደዚ ሲፃፍ አይደል ዴ	neutral
6	አዎ እናንቴ ሽልማት እያላችሁ በኛ ሙድ ያዙ	negative
7	daily pakage መሆን አለበት በትንሹ	positive
8	የስልክ መስመሬ ሃክ ተደርጎ ካርድ ሞልቼ መጠቀም አልቻልኩም ጭራሽ ይበደሩበታል ይሁን በኔ ሲም ወንጀል ሰርተው	negative
9	የኢካፍ አገልግሎት የኢትዮ ቴሌኮም ስርጭትን ለማካተት መስፈርቶቹን እንፈልጋለን	positive
10	አረ በፈጠራቹ አማራና አፋር ክልል የኢትዮ ቴሌኮም አካል አይደሉም እንዴ በጣም ያሳዝናልል እባካቹ ኢንተርኔቱን ል	negative
11	መልካም ስራ ነው	positive
12	ብፓለቲካ ፓርቲ ውጭበራ ከሃይማኖታዊና ከበሄር ፓለቲካ ውጅንበር ከቆኝና ከግራ የፓለቲካ ግርግር የተለየ ህዝባዊ (	neutral
13	safaricom loading	neutral
14	ሽልማቱ ቀረ እንዴ	negative
15	ኮምፒውተር ገዝቼ በሰፈሬ የኢንተርኔት ኬብል የለንም ምን ማድረግ አለብኝ ቴሌዎች	negative
16	ለፈረንጆቹ በአል የኢንተርኔት ቦነስ አትለቁልንም እንዴ	positive
17	ethio telecom እጣው ከምን ደረሰ	positive
18	ያልገባኝ የለን ቴሌ ይሄንን ቴክስት ስትልኩ ከየትኛዎቹ የቴሌ ኩባንያዎቹ ጋር አወዳድረነው እስተያየት የምንሰጠው ባይ	negative
19	cbe ጋር ያለው ችግር የምን ይሁን ቴሌብር ማዘዋወር አልተቻለም	negative
20	አረ wifi ቅናሹን አብራሩልን	positive

Appendix II: Sample of Python Codes

#Python Code to remove punctuation, numbers, and symbols

```
import re
import pandas as pd

# Load the data
data = pd.read_excel('uncleaned.xlsx')

# Ensure the 'Comments' column is treated as a string
data['Comments'] = data['Comments'].astype(str)

# Function to remove punctuation, special characters, numbers, and emojis
def remove_punc_special_chars_and_emojis(word):
    # Compile regex patterns for performance
    pattern = re.compile(r'[!\@#\$%\^«»&\*\(\)…\[\]\{\};“”›’‘"\'\:,.\‹\/<>\?\\\\|`´~\-=\+፡።፤;፦፥፧፨_]')
    numbers_pattern = re.compile(r'[0-9፩፪፫፬፭፮፯፰፱፲፳፴፵፶፷፸፹፺፻]')
    emoji_pattern = re.compile("["
                               u"\U0001F600-\U0001F64F"  # emoticons
                               u"\U0001F300-\U0001F5FF"  # symbols & pictographs
                               u"\U0001F680-\U0001F6FF"  # transport & map symbols
                               u"\U0001F1E0-\U0001F1FF"  # flags (iOS)
                               u"\U00002702-\U000027B0"
                               u"\U000024C2-\U0001F251"
                               "]+", flags=re.UNICODE)
    word = pattern.sub('', word)
    word = numbers_pattern.sub('', word)
    word = emoji_pattern.sub('', word)
    return word

# Apply the punctuation, special characters, numbers, and emojis removal function
data['Comments'] = data['Comments'].apply(remove_punc_special_chars_and_emojis)
```

#Python Code Amharic character level normalization

```python
# Function for character level normalization
def normalize_char(token):
    replacements = {
        '[ኀሐኸ]': 'ሀ', '[ሑኁኹ]': 'ሁ', '[ኂሒኺ]': 'ሂ', '[ኃሓኻ]': 'ሃ', '[ኄሔኼ]': 'ሄ',
        '[ሕኅኽ]': 'ህ', '[ኆሖኾ]': 'ሆ', '[ሠ]': 'ሰ', '[ሡ]': 'ሱ', '[ሢ]': 'ሲ',
        '[ሣ]': 'ሳ', '[ሤ]': 'ሴ', '[ሥ]': 'ስ', '[ሦ]': 'ሶ', '[ዐ]': 'አ',
        '[ዑ]': 'ኡ', '[ዒ]': 'ኢ', '[ዓ]': 'አ', '[ዔ]': 'ኤ', '[ዕ]': 'እ',
        '[ዖ]': 'ኦ', '[ጸ]': 'ፀ', '[ጹ]': 'ፁ', '[ጺ]': 'ፂ', '[ጻ]': 'ፃ',
        '[ጼ]': 'ፄ', '[ጽ]': 'ፅ', '[ጾ]': 'ፆ', '[ቊ]': 'ቁ', '[ኵ]': 'ኩ',
        '[ሗ]': 'ኋ', '(ቱ[ዋአ])': 'ቷ', '(ሩ[ዋአ])': 'ሯ', '(ሱ[ዋአ])': 'ሷ',
        '(ሹ[ዋአ])': 'ሿ', '(ቁ[ዋአ])': 'ቋ', '(ቡ[ዋአ])': 'ቧ', '(ቹ[ዋአ])': 'ቿ',
        '(ሁ[ዋአ])': 'ኋ', '(ኑ[ዋአ])': 'ኗ', '(ኙ[ዋአ])': 'ኟ', '(ኩ[ዋአ])': 'ኳ',
        '(ዙ[ዋአ])': 'ዟ', '(ጉ[ዋአ])': 'ጓ', '(ደ[ዋአ])': 'ዷ', '(ጡ[ዋአ])': 'ጧ',
        '(ጩ[ዋአ])': 'ጯ', '(ጹ[ዋአ])': 'ጿ', '(ፉ[ዋአ])': 'ፏ', '(ሉ[ዋአ])': 'ሏ',
        '(ሙ[ዋአ])': 'ሟ'
    }

    for pattern, replacement in replacements.items():
        token = re.sub(pattern, replacement, token)

    return token
# Apply the character normalization function
data['Comments'] = data['Comments'].apply(normalize_char)

# Save the cleaned data to a new Excel file
output_file = 'cleaned_dataset1.xlsx'
try:
    data.to_excel(output_file, sheet_name='data1', index=False)
    print(f"File saved successfully as {output_file}")
except PermissionError:
    print(f"Permission denied: Could not save the file {output_file}. Please ensure the file is closed and you have write per
except Exception as e:
    print(f"An error occurred: {e}")
```

```
File saved successfully as cleaned_dataset1.xlsx
```

#Python Code stop word removal

In [ ]:

```python
#Python Code Stop-Word Removal
import re import nltk
import numpy as np import pandas as pd
data = pd.read_excel('facebook_twitter_datase.xlsx')

stopwords = pd.read_excel('stopwords.xlsx', header=None) stopwords = stopwords[0].to_list()

data['Comments'] = data['Comments'].astype('str')

data['Comments'] =data['Comments'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stopwords)]))

writer = pd.ExcelWriter(facebook_'twitter_dataset.xlsx', engine='xlsxwriter') data.to_excel(writer, sheet_name='data')
writer.save()
```

#Python Code English Word level normalization

```
import re import nltk
import numpy as np import pandas as pd
data = pd.read_excel('facebook_twitter_datase.xlsx') contractions_dict = {
'didn\'t': 'did not',
'can\'t' : 'can not',
'don\'t' : 'do not',
'doesn\'t' : 'does not',
'that\'s' : 'that is',
'aren\'t' : 'are not',
'isn\'t' : 'is not',
'it\'s' : 'it is',
'couldn\'t' : 'could not',
'hasn\'t' : 'has not',

'10q' : 'thank you',
'pls' : 'please',
'dont': 'do not',
'cant': 'can not',
'plz': 'please', 'coudnt': 'could not', 'shan\'t': 'shall not',
'won\'t': 'will not',}

contractions_re = re.compile('(%s)' % '|'.join(contractions_dict.keys())) def expand_contractions(s, contractions_dict=contra
def replace(match):
return contractions_dict[match.group(0)] return contractions_re.sub(replace, s)
# Expanding Contractions in the reviews data['Comments']=data['Comments'].apply(lambda x:expand_contractions(str(x)))
writer = pd.ExcelWriter(facebook_twitter_dataset.xlsx', engine='xlsxwriter') data.to_excel(writer, sheet_name='data')
writer.save()
```