



JIMMA UNIVERSITY
JIMMA INSTITUTE OF TECHNOLOGY (JIT)
SCHOOL OF COMPUTING
DEPARTMENT OF INFORMATION TECHNOLOGY

BY: - Assefa Nemera Gobena

A Thesis Submitted to the Faculty of Computing of Jimma Institute of Technology
in Partial Fulfillment for the Degree of Master of Science in Information
Technology

Jimma, Ethiopia

June, 2024



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Sentiment Analysis for Afaan Oromo Sentence Classification
using deep learning Approaches

BY: - Assefa Nemera Gobena

Name and Signature of Members of the Examining Board

Name	Signature	Date
Advisor: Getachew Mamo (Ph. D)	_____	_____
Co-adviser: Mr. Dawud Yimer	_____	_____
Chairperson: _____	_____	_____
External Examiner: _____	_____	_____
Internal Examiner: _____	_____	_____

Jimma, Ethiopia

June, 2024



Declaration

I, undersigned, declare that this is my original work, that it has not been submitted as part of a degree requirement at any other university, and that all sources of materials included in the thesis have been properly acknowledged.

Research Thesis Submitted By:

Assefa Nemera Signature _____ Date _____



Acknowledgements

First, I would like to thank the Almighty God, for his uncountable blessings throughout my life and this research. This research work would not have been accomplished without the support of many people. Hence, I would like to express my gratitude to all the people who helped and supported me during this study. I would like to express my deep and honest gratitude to my research advisor, **Dr. Getachew Mamo** for agreed agreeing to supervise my thesis; without his guidance and support, this thesis would not have been successful. I would also like to thank my co-advisor **Mr. Dawud Yimer** for his continual support, encouragement, and patience. I would also like to express my gratitude to all my friends for giving me support and continuous encouragements throughout my thesis. Words are not sufficient to express my love and appreciation to my beloved family for their endless love, care and great support through the duration of my studies. Finally yet importantly, I would express my special thanks to all of my friends for their love, prayers, caring and sacrifices.

Dedication

This thesis is dedicated to my family and to all those who gave me all kinds of support next to GOD



Abstract

Sentiment analysis has recently become one of the growing research fields related to natural language processing and machine learning. An opinion can be positive, negative, or neutral, it depends on each individual's judgment or assessment of a topic. Social media now plays a vital role in influencing people's emotions for or against a government or organization. Therefore, to understand the sentiment of any social media post, an effective method is the ultimate necessity. We analyzed several social media posts to understand social sentiment. Within this broad scope, we performed this research by applying the most advanced sentiment analysis technology on AO using deep learning in the social domain. Subsequent preparation of the dataset on another domain will improve the language. So, in this study, let's try to display data extracted from OBN official page using Social Media Graph Application interface on PR issues and prepare data for the process subsequent preprocessing. Therefore, after crawling from the OBN using the post id, all the pre-processing, tokenization, stop word removal, and phrase stemming steps will be performed. Manual annotation of sentences extracted from data containing both text files and Emojis annotated using language experts into three classes, positive, neutral and negative, see examine the impact of the most popular Emojis. For the classifiers, we used an 80% train and 20% test rule. We used tokenization, stop word removal, normalization, and derivation as preprocessing, and tf-idf was used as feature extraction. Performance of proposed approaches RNN and Transformer models achieve 90% and 91% accuracy on Facebook, Twitter, and YouTube OBN datasets with corpus size of 2051, respectively.

Keywords: Sentiment analysis; Afaan Oromo; Deep Learning, sentence classification; Recursive Neural Network

Table of Contents

Declaration.....	iii
Acknowledgements.....	iv
Dedication.....	v
Abstract.....	vi
Table of Contents.....	vii
List of Table.....	x
List of Abbreviations.....	xii
Chapter One.....	1
1.1 Introduction.....	1
1.2 Background.....	2
1.3. Rationale.....	4
1.3.1 Application of Sentiment Analysis.....	4
1.4 Statement of the Problem.....	4
1.5. Overall Goal.....	9
1.5.2 Specific Objective.....	9
1.6. Methodology.....	9
1.6.1. Data Source Selection and Collection.....	10
1.6.2. Design Approach.....	11
1.6.3. Tools and Techniques.....	12
1.6.4 Evaluation.....	13
1.7. Scope of the study.....	13
1.8 Significance of the study.....	13
1.8.1 Contributions.....	15
1.9 Thesis Structure.....	15
Chapter Two.....	16
2.1 Literature Review.....	16
2.2 Afaan Oromo Language Sentence Classifications.....	17

2.3 Sentiment Analysis in Afaan Oromoo	19
2.4 Deep Learning.....	19
2.5 Types of Deep Learning networks	21
2.5.1 Deep Learning for Sentiment Analysis	22
2.6 Approaches to Sentiment Classification	23
2.6.1 Stages of Sentiment Analysis.....	23
2.6.2 Classification of sentiment analysis	26
2.7 Recurrent Neural Networks (RNN)	27
2.7.1 Recurrent Neural Networks and Long Short-Term Memory (LSTM).....	29
2.8 Sentiment Analysis	30
2.8.1 Techniques of sentiment Analysis	30
2.9 Related Works.....	31
Chapter Three.....	36
3. Designing Sentence Level Sentiment Analysis	36
3.1. Materials and Methods.....	36
3.1.1. Data collection	36
3.1.2. Data preprocessing.....	37
3.1.3. Tokenization	38
3.1.4. Stemming	38
3.1.5. Feature Selection.....	39
3.2. Feature Extraction and Classification	42
3.3. RNN	45
3.3.1. Long-Short-Term Memory Network (LSTM)	49
3.4 Transformers.....	53
3.4.1 Transformer architecture.....	53
3.5 Word Embedding	55
3.6. Development tools	57
Chapter four	58
4. Results and Discussion	58
4.1. Results of the neural networks	66
4.2.1 Recursive Neural Network.....	66

4.1.2.2. Long-short Term Memory	70
Chapter Five.....	71
5.1 Conclusions.....	71
5.2 FUTURE WORK.....	75
Reference	77

List of Table

TABLE 1 ANALYZING SENTIMENT AT THE SENTENCE LEVEL, DOCUMENT-LEVEL AND ASPECT-LEVEL.....	7
TABLE 2 SUMMARY OF REVIEWED PAPERS	34
TABLE 3 THE ARCHITECTURE OF THE TRANSFORMER	54
TABLE 4 HERE'S A DETAILED EXPLANATION OF HOW WORD EMBEDDING WORKS FOR THE SENTENCE "THE CAT SAT ON THE MAT":	56
TABLE 5 CNN CONFIGURATION FOR AFAAN OROMOO SENTENCE CLASSIFICATION	67
TABLE 6 LSTM NETWORK CONFIGURATION FOR AFAAN OROMOO SENTENCE CLASSIFICATION.....	70



List of Figures

FIGURE 1 THE DIFFERENCES BETWEEN TWO CLASSIFICATION MACHINE LEARNING (TOP), AND DEEP LEARNING (BOTTOM).	20
FIGURE 2 CLASSIFICATION OF DEEP LEARNING TECHNIQUES [16]	21
FIGURE 3 LEVEL OF SENTIMENT ANALYSIS (SHELAR ET.AL, (2018))	24
FIGURE 4 TAXONOMY OF SENTIMENT ANALYSIS	26
FIGURE 5 A LONG SHORT-TERM MEMORY NETWORK 1 LSTM, LONG SHORT-TERM MEMORY	28
FIGURE 6 COMPRESSED REPRESENTATION (TOP), UNFOLDED NETWORK (BOTTOM). IMAGE FROM: RNN INTRODUCTION	45
FIGURE 7 AN EXAMPLE OF RNN. IMAGE FROM: HTTPS://WWW.YOUTUBE.COM/WATCH?V=Y2wFIKQYD1I&t=526s .46	
FIGURE 8 RNN NETWORK. IMAGE FROM: HTTPS://AWS.AMAZON.COM/WHAT-IS/RECURRENT-NEURAL-NETWORK	47
FIGURE 9 ACTIVATION FUNCTIONS. IMAGE FROM KAZI, ACTIVATION FUNCTION.....	47
FIGURE 10 TRAINING RNN. IMAGE FROM: WHAT IS RECURRENT NEURAL NETWORK (RNN)? CODE BASICS	48
FIGURE 11 S-LSTM ARCHITECTURE	51

List of Abbreviations

ANN	Artificial Neural Network
AOSA	Aspect-Oriented Sentiment Analysis
AO	Afaan Oromoo
CPU	Central Processing Unit
DL	Deep Learning
DLSA	Document-Level Sentiment Analysis
DTC	Document text classification
GRU	Gated Recurrent Unit
HTML	Hyper Text Markup Language
LSTM	Long Short-Term Memory
ML	Machine Learning
MNB	Multinomial Naïve Bayes
NB	Naïve Bayes
NLP	Natural Language Processing
POS	Part of Speech
RNN	Recurrent Neural Network
SA	Sentiment Analysis
SVM	Support Vector Machine
TC	Text classification
TF-IDF	Term Frequency-Inverted Document Frequency

Chapter One

1.1 Introduction

In today's world all users are using online platform and share their views and opinions and comments regularly. This kind of information can be mined by various machine learning techniques and used efficiently. People are able to express their sentiments in form of posts, comments, tweets, emoticons [1] etc. Due to the rapid development and popularity of social media networks, a huge amount of user-generated content, have been made available online. Identifying and determining whether the attitude of user generated content as positive or negative has become essential for different businesses and social entities as it is important for service providers and vendors to create successful marketing strategies and for the understanding of areas of improvement in products and services [1]. Analysis of opinions plays an important role in all science areas (politics, economics, and social life). For example, in marketing, if the sellers know about the customer's satisfaction with a particular product, they may predict demand on the service or product. The same for politicians, they will know whether people support them or not, the government also understands the will of the society on their policy [1].

Sentiment analysis refers to the management of sentiments, opinions, and subjective text [2]. Sentiment analyses provide comprehension information related to public views, as it analyzes different tweets and reviews. It is a verified tool for the prediction of many significant events such as the box office performance of movies and general elections [2]. Public reviews are used to evaluate a certain entity, i.e., person, product, or location, and might be found on different websites like Amazon. The opinions can be categorized into negative, positive, or neutral. The purpose of sentiment analysis is to automatically determine the expressive direction of user reviews. The demand for sentiment analysis is raised due to the increased requirement of analyzing and structuring hidden information which comes from social media in the form of unstructured data [2].

In natural language processing, text classification is a critical task; it is a behavior of dividing a set of input documents into one or more classes [3]. From a natural language processing point of opinion, students recognize the fundamental structure of the problem and the language hypotheses commonly used to express opinions, sentiments, and emotions. The presence of so

much text in electronic form is a challenge to natural language processing. So, it's better to define a well-defined methodology to analyze and classify this massive data has drawn many communities' attention to this kind of data which is known as unstructured text [3].

Sentiment analysis can be conducted at different levels [3]. The most famous level of sentiment analysis is document level, aspect level, and sentence level. The document level deals with determining the overall opinion of the document expressed by the opinion holder. The aspect level sentiment analysis is the task of extracting the relevant aspects of the reviewed product or entity and determining the sentiment of the corresponding opinion about them. Whereas, the Sentence level sentiment analysis is the more fine-grained analysis of the document [3]. In this, polarity is calculated for each sentence as each sentence is considered a separate unit and each sentence can have different opinions. Sentiment analysis provides unified analytics of customer comments/ feedback by using specific hashtags, mentions, and social media listening, so as you can create and measure customer satisfaction scores based on that. Using these insights, you can devise ways to make a better connection with your audience.

1.2 Background

Natural Language Processing (NLP) is a branch of AI and linguistics concerned with making computers understand statements or words written in human languages [4]. Natural language processing was created to make users' lives easier and to fulfill their desire to connect with computers in natural language [4]. NLP deals with building computational algorithms that can automatically analyze and process human language. NLP-based systems have enabled a wide range of applications like the Google's powerful search engine, and the Amazon's voice assistant named Alexa. NLP also becomes powerful to teach machines the ability to perform complex natural language related tasks such machine translation and dialog generation [4].

There are three machine learning methods or other technologies are used to automatically classify documents [3]. The first is supervised machine learning which the categories are known beforehand and given in advance for each training document. The second method is the unsupervised method, in which documents with similar words or sentences are automatically categorized together by a classifier without any prior training. The last one is Rules-based method; this strategy entails utilizing a system's natural language comprehension capabilities and developing linguistic rules that tell the system to classify a document as if it were a person [3].

The presence of so much text in electronic form is a challenge to natural language processing. So, it's better to define a well-defined methodology to analyze and classify this massive data has drawn many communities' attention to this kind of data which is known as unstructured text. This phenomenon has made the importance of document text classification begins to mechanism up. Text classification (TC) is an automatic mapping of text to a set of predefines categories. It has many important applications like sentiment analysis, sentence classification, and document Classification [3]. Sentiment analysis can be conducted at different levels. The most famous level of sentiment analysis is document level, aspect level, and sentence level. The document level deals with determining the overall opinion of the document expressed by the opinion holder. The aspect level sentiment analysis is the task of extracting the relevant aspects of the reviewed product or entity and determining the sentiment of the corresponding opinion about them. Whereas, Sentence level sentiment analysis is the more fine-grained analysis of the document. In this, polarity is calculated for each sentence as each sentence is considered a separate unit and each sentence can have different opinions [5].

The sentiment analysis is multidisciplinary field, because it includes numerous fields such as computational linguistics, information retrieval, semantics, natural language processing, artificial intelligence and machine learning [6]. Sentiment Analysis can be understood as a text mining technique used to identify and extract subjective insights from unstructured text to help businesses or other organizations to monitor the social sentiment related to their products, brand or services [7].

The polarity of a sentence level only classifies the entire document or sentence; it does not identify the aspects present in the sentence. For example, the document's polarity is positive or negative does not mean that the document has a positive or negative opinion for each aspect. Opinion mining at the aspect level is used to determine people's opinions on various topics. Two aspects can be found. Explicit aspects are nouns and noun phrases that are easily detected in the reviews.

“The voice quality of this phone is excellent,” for example, is an explicit component of her voice quality that can be seen clearly in the sentence [8]. Explicit aspects are nouns and noun phrases that are not easily detected in the reviews. Implicit aspects are nouns and noun phrases that are not easily identified in the reviews. For example, in the statement "This phone does not

fit in my pockets," the implicit aspect "does not fit in my pockets" denotes the aspect size that cannot be stated or recognized in the sentence [8].

1.3. Rationale

A social networking service allows users to create, and share information, and ideas that express sentiment and influence others. With the growth of these social websites, attention is given to information extraction on these messages. Henceforth, due to the high number of users of Afaan Oromo on social media, it needs to understand people's emotions, especially in social media. Choosing to work with the Afaan Oromo language is due to several factors.

First, naturally, people can understand emotions, and analyze the situations and the sentiments associated with them. However, how efficiently can we train a machine to exhibit the same phenomenon becomes a vital question to be explored from the Afaan Oromo language perspective. Second, Afaan Oromo sentiment analysis is important due to its already large-scale audience and huge availability of data on the internet. Finally, yet significantly, most of the tools are available in English and other languages, it is important to build a model for Afaan Oromo to classify the sentiment of the sentence, to reduce the effort of analyzing, suggesting, and providing important information for the user and interested researcher to take this problem as our research work.

1.3.1 Application of Sentiment Analysis

Many requests and likelihoods: The analysis towards politician and government policy and Upcoming elections, a better tool for politicians

- *Governments:* Politicians want to know voters' views and Voters want to know politicians' stances and who else supports them.
- *Advertising:* Consumer attitudes and Trends
- *Customer information:* Product reviews
- *Community:* Find likeminded individuals or community

1.4 Statement of the Problem

In this study, we aim to leverage the power of deep learning techniques for sentiment analysis through sentence classification. The primary objective is to develop a robust and accurate deep

learning model that can effectively classify sentences into sentiment categories with high precision and recall. Feature Extraction is Designing an architecture that can automatically learn relevant features from the input text to capture the sentiment information effectively. Handling Imbalanced data is dealing with imbalanced datasets where one sentiment class may dominate the others, leading to biased models [9, p. 1]. Model Generalization is Ensuring that the model can generalize well to unseen data and different domains, avoiding overfitting on the training set. Interpretable Results create a model that not only predicts sentiment accurately but also provides insights into the reasons behind the classification decisions. Computational Efficiency is Developing a model that is computationally efficient and scalable to handle large volumes of text data in real-world applications. By addressing these challenges and developing a state-of-the-art deep learning model for sentiment analysis through sentence classification, this research aims to advance the field of NLP and contribute to the development of more accurate and reliable sentiment analysis systems.

Sentence Classification focuses specifically on categorizing individual sentences into predefined classes or categories. In the context of sentiment analysis, this typically involves determining the sentiment expressed within a single sentence, irrespective of the sentiment conveyed in the larger context of the document. Sentence classification may be used in scenarios where it's necessary to analyze sentiment on a more granular level, such as parsing social media posts or customer feedback where sentiments can vary from sentence to sentence within the same document. For sentiment analysis of Afaan Oromoo, the choice between text classification and sentence classification depends on the specific use case and the level of granularity required in sentiment analysis [10].

Text Classification is represented using a single word, phrase, sentence, paragraph, or all documents with senses, etc. But when we classify using single-word text in Afaan Oromoo one word may have more than one meaning, and also when we classify using single-phrase text in Afaan Oromoo phrase may not have the full meaning of the given comment and on the other hand using paragraph or all documents also change the meaning of the given since it is having redundant words to put the senses.

we convey that redundant words in documents can affect the meaning and complicate sentiment analysis and text classification. These words demonstrate the richness and flexibility of Afaan

Oromoo's meaning often depends on the context in which the word is used. In sentiment analysis, redundant words in documents can alter the intended meaning, complicating the task of text classification. Here are some examples of Afaan Oromoo words with more than one meaning:

- i. "Jaalala": This word can mean "love" as well as "friendship" depending on the context.

"Jaalala hin qabnu" (We don't have love) and "Jaalala hundaa" (True friendship).

- ii. "Mana": can mean "House" or "Family" depending on the context:

House: "Mana haaraa ijaarrataniiru." (They have built a new house.)

Family: "Mana keenya waggaa lama booda arge." (I saw my family after two years.)

- iii. "Galma": This word can mean both "Goal" and "Palace" depending on the context.

Goal: "Galma kiyya milkeeffachuuf carraaqun barbaachisaa dha." (It is necessary to strive to achieve my goal.) and Palace: "Galma mootii daawwachuun fedha." (I want to visit the king's palace.)

These examples exemplify how a single word in Afaan Oromoo can carry multiple meanings, and the intended sense is often disambiguated by the context in which it is used. This complexity underscores the challenge of text classification in languages where words can have varied interpretations.

- Here are some examples of phrases in Afaan Oromoo that can have multiple meanings depending on the context:

- i. "Eeboo dachee qabna": This phrase can mean both "Eeboo is angry" and "Eeboo is busy":

"Eeboo dachee qabna, hin dhorkiin irra" (Eeboo is angry, don't provoke him).

"Eeboo dalagaa qabna, Boodan itti dubadha" (Eeboo is busy, I'll talk to him later).

- ii. "Lafti isaa faaya" This phrase can mean both: His land is fertile. ("Lafti isaa faaya.") and His ground is beautiful. ("Lafti isaa bareedaa dha.")

These examples demonstrate how phrases in Afaan Oromoo can carry different meanings depending on the context in which they are used, highlighting the importance of considering the surrounding context for accurate interpretation. The sentence level sentiment analysis is closely related to subjectivity analysis. At this level, each sentence is analyzed and its opinion is determined as positive, negative, or neutral.

Enhancing the accuracy of DLSA and AOSA by ensuring that only subjective sentences contribute to sentiment scores. DLSA can benefit from sentence-level analysis by aggregating sentiment scores of subjective sentences and AOSA can use sentence-level analysis to identify and extract specific aspect-related sentiments from relevant subjective sentences. Therefore, DLSA provides a broad sentiment classification for entire documents. AOSA offers detailed sentiment analysis for specific aspects or features within the text and Sentence-level sentiment analysis helps in distinguishing subjective content, enhancing the accuracy of both DLSA and AOSA.

Analyzing sentiment at the sentence level indeed offers several advantages over text-level or aspect-level sentiment analysis, particularly in terms of capturing nuanced opinions in short messages. Here are some key reasons.

Table 1 Analyzing sentiment at the sentence level, Document-Level and Aspect-Leve

Granularity of Sentiment	
Sentence-Level	Allows for identifying specific sentiments expressed in each sentence, leading to a more detailed thoughtful of the text. Customer feedback analysis, and social media monitoring where short, sentence-length messages are common
Document-Level	Averages the sentiment across the entire text, potentially missing conflicting sentiments within different parts of the text. More suitable for summarizing overall sentiment in longer documents but less effective for detailed insights.
Aspect-Leve	Focuses on specific aspects or topics but might overlook the overall sentiment expressed about those aspects in different sentences.
Contextual Understanding	
Sentence-Level	Each sentence can be analyzed within its own context, leading to more accurate sentiment detection. Sarcasm, irony, or shifts in tone can be better identified. Can

	capture and differentiate mixed sentiments within a single text. For example, a review might have positive and negative sentences.
Document-Level	Loses the contextual nuance of individual sentences. Tends to dilute mixed sentiments into a single score, which can be misleading.
Aspect-Level	Provides context for specific aspects but might miss overall sentiment trends. Identifies sentiments related to specific aspects but may miss the context provided by individual sentences.

Sentence-level sentiment analysis offers a fine-grained (at a very detailed level), contextually aware approach that is particularly effective for analyzing short messages and capturing nuanced opinions. It strikes a balance between the broad overview provided by text-level analysis and the detailed aspect-specific insights offered by aspect-level analysis.

While Document-Level Sentiment Analysis (DLSA) and Aspect-Oriented Sentiment Analysis (AOSA) focus on different scopes of text, sentence-level sentiment analysis is another granularity that deals with individual sentences within a text and classifies sentences as subjective or objective.

Subjective sentences express personal feelings, views, emotions, or beliefs and carry a sentiment polarity (positive or negative).

Objective sentences present factual information without sentiment and filtering out objective sentences to focus on subjective content that carries sentiment.

By focusing on sentence-level sentiment analysis, businesses, and social entities can gain deeper insights into user opinions and sentiments, leading to more effective and timely decision-making. One problem is that there is no standard set of information to use for studying people's feelings in different areas like politics, business, entertainment, and transportation. Using different solutions for sentiment analysis is not a good idea because we need different tools and models for different situations. Sentiment analysis is a popular task in natural language processing that involves studying texts, like posts and reviews on social media and online shopping sites, to understand what people think about a product, service, event, or person. The scientists suggested using RNNs and Transformer models to study how computers can automatically classify sentences. So, in this research, we used deep recurrent neural networks to analyze the feelings in

Afaan Oromoo sentences. We wanted to understand the emotions at a detailed level. Finally, the research will try to find answers to these questions:

- How to accurately analyze people's feelings about Army Officers in individual sentences?
- How do we use deep learning to analyze feelings on Facebook, Twitter, and YouTube using RNNs and the Transformer Model to do sentiment analysis?
- How can we check which Deep Learning model shows the most feelings using adverbs and adjectives?

1.5. Overall Goal

This study aims to create a way to analyze the feelings in Afaan Oromoo sentences using deep learning

1.5.2 Specific Objective

The following specific task was going to be done to meet the study's main objective:

- To design a deep learning approach for Afaan Oromoo Sentiment analysis at the Sentence Level.
- To see how well RNN and Transformer Model algorithms test sentence feelings in the AO.
- To compare and contrast the testing of RNN & Transformer Model algorithms on Sentence-level sentiment analysis of AO.
- Design a model for Sentiment analysis to classify social media Sentences for Afaan Oromoo.
- Create a plan to figure out how people feel about things on social media in Afaan Oromoo.

1.6. Methodology

Constraint identification and classification through a structured approach is a productive way to test out different algorithms that are offered by Sentiment Analysis. This study first reviewed various types of Sentence analysis to determine and distinguish the structure of the researcher what sources of data we used, which tools and algorithms are used, and how the analysis and evaluation of the discovered knowledge will be done.

For the development of an effective sentiment analysis system for Afaan Oromo sentence classification, collecting high-quality data is dominant. The data used in this study was sourced from the official page of the Oromia Broadcasting Network (OBN). This approach has several advantages

1.6.1. Data Source Selection and Collection

The researcher used OBN Media's official social media pages as the primary source of data, complying with the legal rules and conditions allowing freedom of expression on social media platforms. The research focuses on two main aspects of social media: community relations. Data was collected from Facebook, Twitter, and YouTube to retrieve comments and posts analyze text data, and download comments by post ID. For public pages, personal politician pages, activist pages, news pages, and various group pages. Publications and commentaries from different chronologies ensure a diverse and complete corpus of documents. Text data was collected from various OBN social media sites to reach online audiences. OBN is a reputable and widely recognized source of news and information in the Oromia region. By collecting data from OBN's official page, we ensure that the content is trustworthy and reliable. The content on OBN's official page is highly relevant to the Afaan Oromo-speaking community. This relevance ensures that the collected data reflects current topics, sentiments, and issues pertinent to native speakers. Using a credible source like OBN helps ensure that the dataset is representative of the language as it is used in various contexts, including news, public opinion, and social commentary. This representativeness is crucial for training models that generalize well to real-world applications.

1.6.1.1 Data Processing and Analysis

The collected data undergoes several stages of processing and analysis to ensure accurate classification and tagging: Text Sample Testing: The model is tested on multiple text samples to evaluate its performance. The goal is to classify and tag the text samples efficiently and accurately.

Classification: The text data is classified based on the focus areas: community relations and conflict. Advanced text processing techniques are employed to analyze the sentiments and topics within the collected comments and posts.

By following this methodology, the researcher aims to build a robust corpus that reflects the dynamics of community relations and conflict on social media, providing valuable insights into online discourse in regions with limited Internet penetration.

This version clarifies the methodology and processes involved, making it easier for readers to understand the research approach and its significance.

1.6.2. Design Approach

The model for developing sentence-level sentiment analysis on AO social media utilizes a deep learning approach, specifically employing Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks.

Deep Learning Approach: Due to the complex and variable nature of sentiment in social media texts, deep learning is chosen for its ability to capture intricate patterns and contextual dependencies. LSTM networks, a type of RNN, are used for their effectiveness in handling long-range dependencies and mitigating the vanishing gradient problem, making them suitable for understanding the context in sequential data like sentences.

Data Preprocessing: **Text Cleaning:** Remove noise such as special characters, URLs, and unnecessary whitespace. **Tokenization:** Break down sentences into individual words or tokens. **Normalization:** Convert text to lowercase and apply stemming or lemmatization to reduce words to their base forms. **Feature Extraction:** **Embedding Layer:** Use pre-trained word embeddings (e.g., Word2Vec, GloVe) to convert tokens into dense vectors representing their semantic meaning. **Sequence Padding:** Ensure uniform input length by padding shorter sequences and truncating longer ones. **Model Architecture:** **Embedding Layer:** Converts input tokens into dense vectors.

LSTM Layer(s): Capture sequential dependencies and context within the text. Multiple LSTM layers can be stacked for better representation learning. **Fully Connected Layer:** Aggregates features extracted by the LSTM layers. Uses a SoftMax or sigmoid activation function to output sentiment classification (e.g., positive, negative, neutral). **Transformer Models:** Implement transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) for capturing long-range dependencies and contextual information in sentences

Evaluation Metrics: Accuracy, precision, recall, and F1-score are used to evaluate model performance on a validation set. *Regularization:* Apply techniques such as dropout to prevent overfitting. Annotate the collected data for sentiment labels. This might involve manual labeling or utilizing pre-labeled datasets if available. *Model Training:* Split the data into training, validation, and test sets. Train the LSTM model on the training set while validating on the validation set to monitor performance. *Model Testing:* Evaluate the final model on the test set to ensure it generalizes well to unseen data. *Deployment:* Deploy the trained model to analyze and classify sentiments in real-time on AO social media platforms. By following this design approach, the deep learning model aims to provide accurate and efficient sentence-level sentiment analysis, effectively capturing the complex and dynamic nature of sentiments expressed in social media interactions.

1.6.3. Tools and Techniques

In this paper, there are three components: preprocessing, feature extraction, and emotion classification. Preprocessing includes removing unnecessary text, symbols, and characters and includes normalizing characters and short forms. This mission is done Using Python programs. The process comment is then embedded using the word2vec method. The remaining component, feature extraction, must be performed using an RNN, and the classification process is performed using a CNN.

1.6.3.1 Preprocessing

The preprocessing phase includes cleaning and normalizing the text data. This can be done in Python in Google Colab. This process includes removing unnecessary text, symbols, and characters as well as standardizing characters and short forms. Embed text data using the Word2Vec method to convert text to a digital representation. Feature extraction involves using an RNN (LSTM) to extract features from embedded text data. Sentiment classification involves the use of transformer (BERT) models for sentiment classification. Text classification is a process of providing labels to a set of texts or words in the form of unique, zero, or pre-defined labels and these labels will tell us the sentiment of the set of words. Transformer models assign sentiment labels to text samples, such as positive, negative, or neutral, based on the extracted features. Text classification, in this context, refers to the process of assigning pre-defined labels

to text data. These labels tell us the sentiment of the text (e.g. positive, negative, neutral). The classification process includes.

1.6.4 Evaluation

For the evaluation of sentiment classification using regular expression is usually measured by precision, recall, and F-measure. Precision is the fraction of relevant retrieved instances, while the recall is the fraction of retrieved relevant instances. F-measure is also used to fairly treat recall and precision, which brings recall and precision into a single measure. Therefore, precision, recall, and F-measure will be used based on an understanding and measure of relevance.

1.7. Scope of the study

The study's focus is on sentiment analysis of Afaan Oromoo Sentence Classification of social media from the OBN, with an emphasis on sentiment analysis for polarization into positive, negative, and neutral categories. The research was done based on data collected from the OBN official page of Afaan Oromoo. Specifically, we focus on OBN Facebook, Twitter, and YouTube people's public relations. Currently, in our country, people are expressing their feelings freely on social media through different mechanisms like text, emojis, pictures, and voice. In this study, we treat only Sentence-based user-generated content. It includes both subjective and objective categorization. Just analyze sentiment at the Sentence level and the approach to meet our study goal included word embedding and deep neural networks. This study is not cornered with aspect-level sentiment analysis and question-answering related opinions. Since the sentiment is highly domain-dependent, this study only deals with specific open relatives' domains. The view holder identification and reasons for positive and negative classifications are not covered in this work.

1.8 Significance of the study

In the contemporary digital landscape, social media platforms globally, including in Ethiopia, are rife with expressions that often include insults, demeaning comments, and devaluation of others. This behavior is inhumane and disrupts the social fabric. Implementing sentiment analysis at the feature level can create a monitored environment where the tolerance and exercise of humane communication are ensured.

Importance of Sentiment Analysis: Informed Decision-Making: Commercial and Political Spheres: Understanding public sentiment is crucial for logical decision-making. By analyzing large volumes of data automatically, stakeholders can gauge public emotions and reactions, aiding in strategic planning and policy formulation. Efficiency and Effectiveness: Data Handling: Given the vast amount of data generated daily on the internet, manually reaching, processing, and analyzing sentiment is impractical. Automated sentiment analysis tools streamline this process, making it feasible to interpret and act upon vast datasets. Application for Various Stakeholders: Individuals: Users can quickly ascertain public opinions on diverse topics such as social issues, government performance, sports, news, and services, enhancing their understanding and decision-making processes.

Organizations and Governments: These tools are invaluable for analyzing public sentiment towards social linkages, identifying ideological biases, and evaluating opinions on policies, political parties, and government agencies. This analysis helps mitigate negative perceptions and bolster activities that foster positive sentiments.

Strategic Advantages: Policy and Service Improvement: Governments can adapt strategies based on sentiment analysis to improve services and meet citizens' needs effectively. Public Opinion Monitoring: Regular sentiment analysis helps in monitoring public opinion dynamically, allowing for timely interventions and adjustments. Research Contribution: This research investigates sentiment analysis for AO Sentence Classification within the social linkage domain. The findings will help build comprehensive opinions that can be utilized in mining systems for the AO language. Practical Applications: The outcomes will serve as critical input data for recommender systems and opinion retrieval/search systems, significantly enhancing their utility and effectiveness.

In conclusion, the research on sentiment analysis for Afaan Oromoo Sentence Classification holds immense value for governments, public organizations, and individuals by providing a tool to better understand and respond to public sentiments. This contributes to more informed decision-making, efficient data handling, and improved public services.

1.8.1 Contributions

The primary objective of this research is to investigate classification algorithms for extracting sentiments from Online Behavior Network (OBN) social linkage data, with a particular emphasis on Recurrent Neural Network (RNN) methods. The research aims to fill the resource gap in sentiment analysis for the Afaan Oromoo language by developing a glossed corpus of sentiment data and conducting experiments to evaluate the performance of these algorithms in detecting positive, negative, and neutral comments/reviews. The study involves the use of Recursive Neural Networks that convert words into word embeddings, which are then processed through multiple layers to determine the polarity of the comments. This approach leverages the capabilities of neural networks to handle large datasets, detect complex relationships between variables, and achieve high learning levels due to their deep structures.

- Corpus Development: Creation of a glossed corpus specifically made-to-order for sentiment analysis in the Afaan Oromoo language, addressing a significant resource limitation.
- Algorithm Evaluation: Systematic experimentation with RNN-based methods to assess their effectiveness in sentiment classification for a low-resource language.
- Sentiment Analysis Advancement: Enhancing the understanding and application of neural networks in sentiment analysis, particularly for languages with limited computational resources and datasets.

Benefits of Neural Networks in Sentiment Analysis

- Scalability: Ability to handle large datasets efficiently.
- Complex Relationship Detection: Capability to uncover intricate patterns and relationships between variables in the data.
- High Learning Capacity: Potential to achieve advanced learning outcomes due to the deep and layered structure of neural networks.

1.9 Thesis Structure

Relevant background theory and fundamental concepts involved in the sentiment analysis, in addition to the tools and data sets used, are described in Chapter 2. Chapter 3 describes the methodologies used in the sentiment analysis for Afaan Oromoo Sentence Classification.

Chapter 4 describes the detailed implementation of related technologies like word segmentation, word embedding, and Recurrent Neural Networks, pooling, and SoftMax. Experiments conducted on these systems and their results are presented in Chapter 5. Finally, Chapter 6 concludes the study and suggests future work.

Chapter Two

2.1 Literature Review

The presence of social media has given increase to a widespread ocean of consumer-generated content data, plentiful in opinions and emotions. Analyzing this data, particularly in under-resourced languages like Afaan Oromoo, offers valuable insights into public sentiment and online conversations. This literature review examines the current state of sentence-level sentiment analysis for Afaan Oromoo text using deep learning approaches, identifying gaps and paving the way for future research. Several studies have attempted Afaan Oromoo sentiment analysis using machine learning techniques like Support Vector Machines and Random Forests. These studies mostly focused on document-level analysis, achieving moderate accuracy. Deep learning Afaan Oromoo sentiment analysis, recognizing the limitations of traditional methods, recent research has embraced deep learning models for Afaan Oromoo sentiment analysis.

The study by author [10] explored the application of Long Short-Term Memory (LSTM) networks for sentiment classification of Facebook comments, achieving promising results in categorizing sentiments as positive, negative, or neutral. The LSTM model demonstrated effectiveness in handling the nuances and complexities of social media text, which often includes slang, abbreviations, and informal language. However, it also highlights important limitations that need to be addressed to enhance the robustness and applicability of such models in diverse contexts. Future research could focus on addressing these limitations by exploring more diverse datasets, improving contextual understanding, and optimizing computational efficiency.

Similarly, by author [1]. demonstrated that CNNs are effective for sentiment classification tasks, leveraging their strength in feature extraction. However, the study also highlighted important limitations, particularly regarding contextual understanding and the complexity of model tuning. Future research could focus on combining CNNs with other models like LSTMs or transformers

to capture both local and global features, improving generalizability, and optimizing computational efficiency.

On another hand by the author, [11] Deep learning holds significant promise for improving the processing and analysis of Afaan Oromoo news articles. It offers advancements in language understanding, translation, summarization, and sentiment analysis. However, challenges such as data scarcity, high computational requirements, model interpretability, and language-specific complexities must be addressed to fully realize this potential. Leveraging transfer learning, data augmentation, and developing dedicated resources can help mitigate some of these limitations, paving the way for more effective and fair applications of deep learning in the context of Afaan Oromoo. This discussion highlights both the potential and the limitations of using deep learning for processing news articles in Afaan Oromoo, grounded in the insights from Yao et al. (2016).

Sentences often express diverse and sometimes conflicting emotions, which are lost in document-level analysis. Therefore, shifting the focus to sentence-level analysis becomes crucial for understanding the intricate nature of online opinions in Afaan Oromoo.

Despite the promising initial results, deep learning-based Afaan Oromoo sentiment analysis faces several challenges. The lack of large-scale labeled datasets, the morphological complexity of the language, and limited research resources pose significant hurdles. However, these challenges also present exciting opportunities for developing innovative solutions. Exploring multilingual transfer learning techniques, leveraging active learning for efficient dataset labeling, and incorporating Afaan Oromoo-specific linguistic features within models can be promising avenues for future research.

2.2 Afaan Oromo Language Sentence Classifications

Afaan Oromo is a Cushitic language spoken by about 40 million people in Ethiopia, Kenya, Somalia, and Egypt. It is the third most widely spoken language in Africa, after Arabic and Hausa. Stance classification has been defined as automatically detecting whether the author of a piece of text is in favor of the given target or against it. Stance is defined as the expression of the speaker's standpoint and judgment toward a given proposition. Stance detection plays a major role in analytical studies measuring public opinion on social media, particularly on political and social issues. The nature of these issues is usually controversial, wherein people express

opposing opinions toward differentiable points [12]. Stance detection has been used to study public opinion in situations such as referendums and elections on political topics. Based on [12] a growing body of work has used the concept of stance detection on social media as a new frontier to analyze various social and political issues across social media platforms. Based on [12] stance classification is usually considered a sub-problem of sentiment analysis and aims to identify the stance of the text author towards a target (an entity, concept, event, idea, opinion, claim, topic, etc.) either explicitly mentioned or implied within the text.

Sentiment analysis using deep learning models has gained significant attention in the field of natural language processing, and it has been applied to various languages, including African languages. This process involves assigning either positive or negative values to the opinion expressed in a specific text, which is especially relevant in the context of social media, news, blogs, and forums.

Let's take Amharic as an example (a language spoken in Ethiopia), where these models have been combined with word embedding techniques for sentence-level sentiment classification of social media messages. The researchers used the Amharic Twitter dataset, consisting of around 3000 text snippets. They applied data augmentation to increase the dataset for training these models and achieved an accuracy of 82.2% using the sentence transformer and cosine similarity on the Amharic corpus.

The exact approach and the effectiveness can vary depending on the specific African language and the available data. Current research and development in this area continue to advance, giving us cause to expect even more sophisticated and accurate models for African language sentiment analysis in the future.

Sentimental Short Sentences Classification by Using CNN Deep Learning Model with Fine Tuned Word2Vec.

Recurrent Neural Networks (RNN) are a type of artificial neural network designed to recognize patterns in sequences of data, such as text, genomes, handwriting, or spoken words. Unlike feed forward neural networks, RNNs can use their internal state (memory) to process sequences of inputs, making them extremely effective for tasks where context from prior inputs is important.

The concept behind RNNs is that they perform the same task for every element in a sequence, with the output being dependent on the previous computations. This loop of operations allows information to be carried across from step to step, creating a form of “memory.” However, standard RNNs can struggle with maintaining context over long sequences, a problem often addressed by using variations of RNNs such as LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Units), which use gating techniques to mitigate the issue of retaining context over longer sequences.

2.3 Sentiment Analysis in Afaan Oromoo

Only a few attempts have been made to analyze the sentiments of the Afaan Oromoo language. We have seen only three studies on sentiment analysis by Afaan Oromoo and six articles. The author by [14] conducted the first study on sentiment analysis of social media content of Afaan Oromoo using machine learning methods. According to the author's report, the method gives good results. However, the lack of linguistic resources such as Part of Speech (POS) and vocabulary databases made the job difficult.

An additional study was also conducted by [14] using the unsupervised method for Afaan Oromo sentiment mining. They experiment on unigram, bigram, and trigram features. Based on the experiment unigram and bigram feature gets high recall and precision respectively. Another study was conducted by [14], on sentiment analysis for Afaan Oromoo using a machine learning approach. Their study was undertaken on document-level sentiment analysis. They reported that the result is promising. However, to the best of our knowledge, there is still no study conducted on character-level multi-scale sentiment analysis using a combination of CNN-Bi-LSTM for Afaan Oromoo. The lack of resources such as lemmatization and morphological analysis tools for the language makes difficult errors, especially in sentiment analysis.

2.4 Deep Learning

Deep learning neural networks, or artificial neural networks, attempts to mimic the human brain through a combination of data inputs, weights, and bias. These elements work together to accurately recognize, classify, and describe objects within the data.

Deep learning adapts a multilayer approach to the hidden layers of the neural network. In traditional machine learning approaches, features are defined and extracted either manually or by

making use of feature selection methods. However, in deep learning models, features are learned and extracted automatically, achieving better accuracy and performance [15]. Figure 1 shows the differences in sentiment polarity classification between the two approaches: traditional machine learning (Support Vector Machine (SVM), Bayesian networks, or decision trees) and deep learning. Artificial neural networks and deep learning currently provide the best solutions to many problems in the fields of image and speech recognition, as well as in natural language processing. In deep learning models, features are learned and extracted automatically, achieving better accuracy and performance. In general, the hyper parameters of classifier models are also measured automatically.

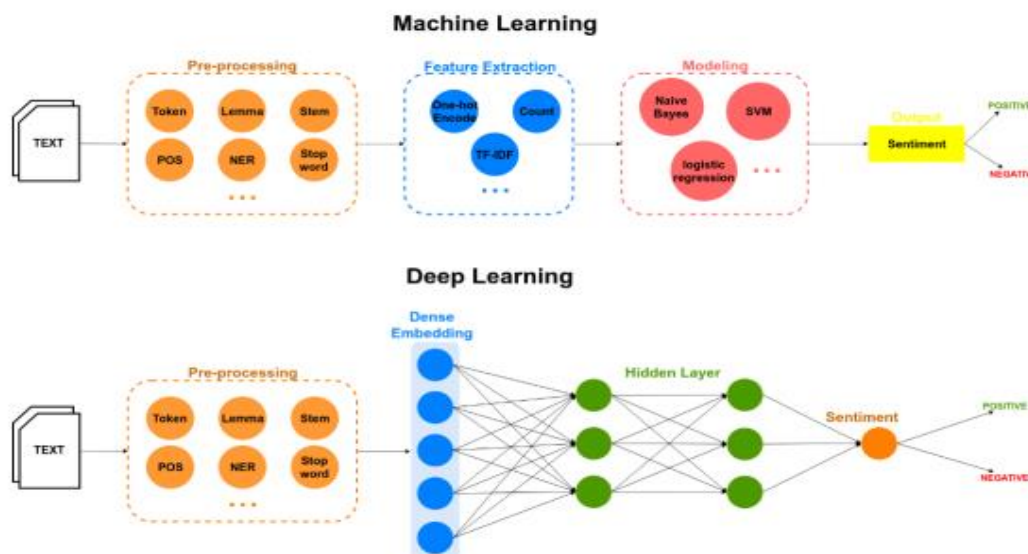


Figure 1 The Differences between two classification machine learning (top), and deep learning (bottom).

Deep Learning is implemented by neural networks, with many layers that are not something new. However, it has become popular recently, due to three factors: First, there is a notable increase in processing capabilities (e.g., video cards, graphical processors, etc.); second, by affordable computer hardware; and third, due to recent advances and developments in Deep Learning research. Deep learning algorithms may be classified into three subgroups, which depend on the fact if the algorithms are trained to yield the obtainable results or not. The three subgroups are classified as unsupervised, supervised and hybrid. The constancy of each of the Deep Learning algorithms has been described in detail [16] (Fig. 2)

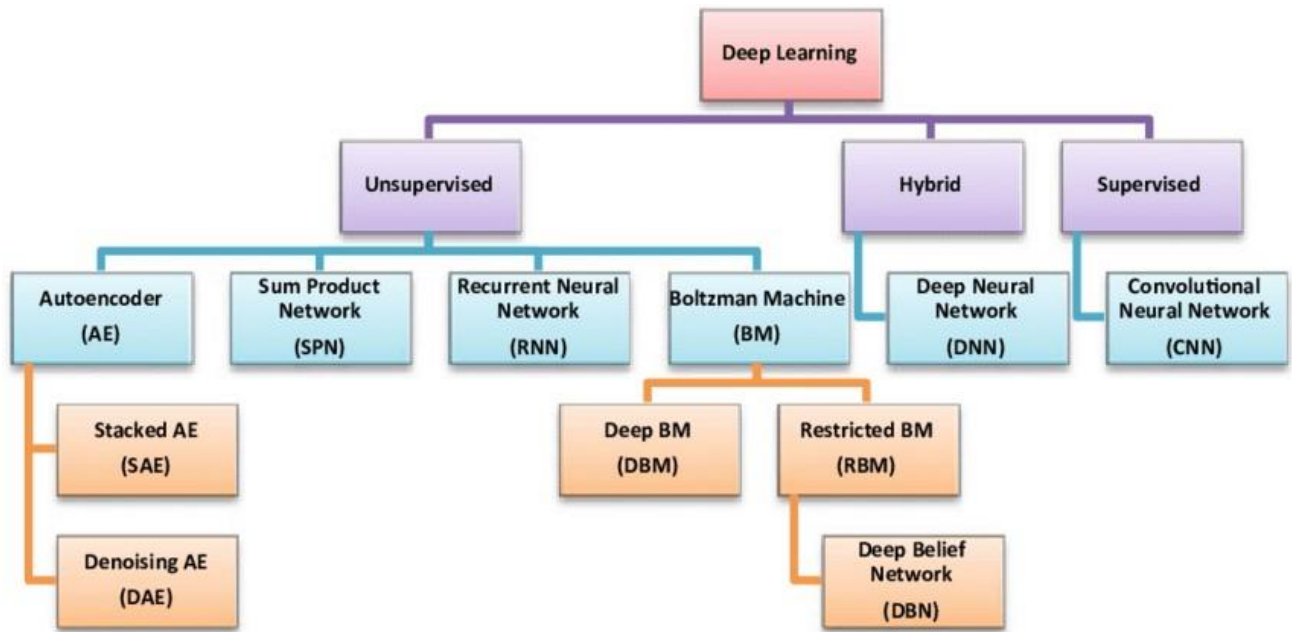


Figure 2 Classification of deep learning techniques [16]

2.5 Types of Deep Learning networks

Deep learning is a broad and comprehensive term used for artificial intelligence and machine learning. Deep learning techniques have achieved high levels of success in a diverse and distinct range of areas of application. But the research community lost its interests in the late 1990s in neural networks. Where neural networks are useful in generating text classification and sentence modeling. Also, deep learning networks have the ability to provide training to supervised and non-supervised groups. Machine learning is part of artificial intelligence that automatically adds benefits from concepts and knowledge to the system for learning without being directly and explicitly programmed. Deep learning algorithms provide opportunities to extract complex data with a high level of abstraction, mainly because they are considered practical only for shallow neural networks "(Neural or two-layer neural networks) as an exercise of a" deep "neural network (neural networks with more layers) is complex and extremely mathematically expensive. Deep learning includes many networks such as CNN (convolutional neural networks), RNN (recurrent neural networks), recursive neural networks, DBN (deep belief networks) and many more.

The most famous types of deep learning networks are including recursive neural networks (RNNs), and CNNs were briefly explained in this section while CNNs where it is the most used

in several applications among other networks. The different types of neural networks in deep learning, such as convolutional neural networks (CNN), recurrent neural networks (RNN), artificial neural networks (ANN), etc. are changing the way we interact with the world. These different types of neural networks are at the core of the deep learning revolution, powering applications like unmanned airborne vehicles, self-driving cars, speech recognition, etc.

2.5.1 Deep Learning for Sentiment Analysis

The author [17] investigated the first work on Convolutional Neural Networks to provide a simple and effective architecture of text classification. After this investigation, various improved models based on Convolutional Neural Networks have been proposed. Santos and Gatti proposed Sentiment Analysis of Short Texts using deep convolutional neural networks (CNN) approach. This proposed deep CNN draws information from character up to sentence level. They proposed Character Sentence Convolutional neural network (CharS CNN). This CharS CNN uses two convolutional layers to obtain related features from any size of words and sentences. They experimented on two corpora, the Stanford Sentiment Treebank (SSTb), which holds movie reviews sentence; and the Stanford Twitter Sentiment corpus (STS), which contain sentence taken from Twitter messages. According to their report, they achieved 85.7% accuracy for the SSTb corpus and 86.4% accuracy for the ST's corpus.

In the combination of convolutional neural network and recurrent neural network was applied for sentiment analysis of the short text. They intended to take advantage of the coarse-grained local features produced by Convolutional Neural Networks as input for RNN and long-term dependencies learned by Recurrent Neural Networks for sentiment analysis output. They experiment on MR, SST1, and SST2 corpora. Additionally, the author proposed Deep CNN-LSTM for IMDb Review Sentiment Analysis with Combined Kernels from Multiple Branches. Review moreover, proposed sentiment analysis for a movie by combining CNN and Bi-LSTM as a complex model. They have designed a suitable structure to combine CNN and Bi-LSTM and to find out the most optimal layer. They have also conducted six experiments for the test and accuracy comparison including single CNN and Bi-LSTM. However, CNN-Bi-LSTM achieved 89.7% accuracy, which is better than single CNN and Bi-LSTM. Furthermore, CNN with one convolutional and pooling layer outperformed CNN with more layers. Likewise, conducted their study on sentiment analysis from Twitter by Multi-Channel lexicon integrated with CNN-Bi-

LSTM. Their study was accompanied by document-level sentiment analysis. They applied a multichannel technique to the lexicon to improve the feature lexicon. They have used word2vec word embedding.

2.6 Approaches to Sentiment Classification

Text classification describes a general class of problems such as predicting the sentiment of tweets and movie reviews, as well as classifying emails as spam or not. Deep learning methods are proving very good at text classification, achieving state-of-the-art results on a suite of standard academic benchmark problems.

2.6.1 Stages of Sentiment Analysis

Analyzing sentiment entails determining polarity for the target object across different levels. The key levels encompass document level, sentence level, and aspect-based analysis. The subsequent section provides as follow.

2.6.1.1 Sentence-Level Sentiment Analysis

Sentimental analysis at the sentence level works with the classification of subjectivity which classifies the sentence given as a subjective or objective sentence. A subjective sentence expresses personal feelings, views, emotions, or beliefs which carry a category of positive or negative polarity, whereas an objective sentence presents some factual information.

2.6.1.2 Document-Level Sentiment Analysis

This method retrieves sentiment from the entire review and categorizes the entire opinion based on the overall sentiment of the opinion holder. When a document is authored by a single individual and conveys sentiment about a specific entity, document-level classification is most effective. It categorizes the entire sentence as positive, negative, or neutral.

2.6.1.3 Aspect-Oriented Sentiment Analysis

Aspect-Oriented Sentiment Analysis (AOSA) is a text analysis approach that dissects data into aspects and assesses the sentiment linked to each aspect. Customer opinions can be scrutinized through aspect-based sentiment analysis, connecting distinct emotions with various features of a product or service. This form of sentiment analysis can extract sentiments and aspects separately. Sentiments revolve around positive or negative feelings regarding a particular subject, while aspects delineate a category, characteristic, or topic under discussion.

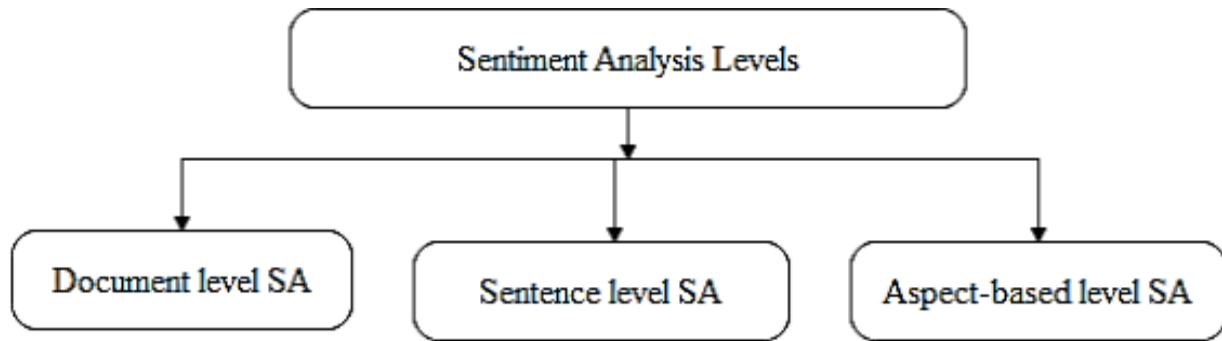


Figure 3 Level of Sentiment Analysis (Shelar et.al, (2018))

The sentence-level polarity finding aims to a detection of sentiment in a sentence. In this task, we assume that the sentence contains only one view towards one entity [18]. One sentence can be considered as a single document, thus similar or identical approaches to document-Level task can be applied. The sentence-level polarity detection task can be used for longer documents in which each sentence is evaluated independently as one document, which results in a set of sentences with assigned sentiment. Alternatively, the assigned sentiments can be summarized to represent the overall sentiment of the document.

Liu [18] defines the sentence-level polarity detection as follows: given a sentence x , determine whether x expresses a positive, negative or neutral view. If there is no opinion the sentence is considered as neutral. He also mentions two possible ways how to solve this problem. The first one is to represent the task as a classical three-class classification problem. In the second approach, he first decided whether the sentence expresses an opinion or not, which is the subjectivity classification task. The second step is then to classify the subjective sentence into a positive or negative class. The first step can be problematic for some sentences because, as we mentioned, even the objective sentence can imply opinions.

For most cases in practice, the sentence-level and document-Level polarity detection is suitable for short reviews, Twitter or Facebook posts or other short text with one or few sentences expressing one opinion towards one entity [18].

The first change we made was the way we train our Bayesian models. Instead of training and classifying at the granularity of the whole document, we are now training and classifying at the sentence level. Here are some of the advantages. It is easier to assign a label to a single sentence

(or in-context expressions) than an entire document, so we can crowd-source labels for our training sets. Over the years, academic research produced freely available labeled datasets for sentiment analysis evaluation. Most of these are at the sentence level so we can incorporate them into our training sets. We can use sentence-level sentiment together with named entity and keyphrase extraction to provide entity-level sentiment (ELS) [19].

We then decided to aggregate the sentence-level sentiment into document-level sentiment via a stacked classifier “picking” the sentiment of meaningful sentences to produce the sentiment for the entire document (a rudimentary but effective form of attention).

The modus operandi for text classification involves the use of a word embedding for representing words and a Recursive Neural Network (RNN) for learning how to discriminate documents on classification problems [19].

Deep learning for natural language processing, comments that neural networks in general offer better performance than classical linear classifiers, especially when used with pre-trained word embedding [20]. The nonlinearity of the network, as well as the ability to easily integrate pre-trained word embedding, often leads to superior classification accuracy. Networks with convolutional and pooling layers are useful for classification tasks in which we expect to find strong local clues regarding class membership, but these clues can appear in different places in the input. We would like to learn that certain sequences of words are good indicators of the topic, and do not necessarily care where they appear in the document. Convolutional and pooling layers allow the model to learn to find such local indicators, regardless of their position [19].

Sentiment analysis is a field within Natural Language Processing (NLP) concerned with identifying and classifying subjective opinions from the text. Sentiment analysis ranges from detecting emotions (e.g., anger, happiness, fear), to sarcasm and intent (e.g., complaints, feedback, opinions). In its simplest form, sentiment analysis assigns a polarity (e.g., positive, negative, neutral) to a piece of text [21]. Melt water has been providing sentiment analysis powered by machine learning for more than 10 years. In 2009, we deployed our first models for English and German [21]. We cannot afford to go much slower than that. Traditional machine learning methods such as Naïve Bayes, Logistic Regression, and Support Vector Machines (SVM) are widely used for large-scale sentiment analysis because they scale well. It has now

been proven that Deep Learning (DL) methods achieve better accuracy on a variety of NLP tasks, including sentiment analysis, however, they are typically slower and more expensive to train and operate [21].

Sentence level Sentiment Categorization: One of the key directions in the sentiment field of analytics is sentence-level sentiment detection. The past research on the subject focused on identifying a sentence's polarity (e.g., positive, neutral, or negative), using semantic information gleaned from the sentences' text information.

2.6.2 Classification of sentiment analysis

Sentiment analysis is performed on human opinion or comments for a product, a service, or an event through social media, websites, emails or other platforms. Since a text of evaluations or comments may have multiple meanings, sentiment analysis can be challenging. Sentiment analysis is performed using text mining with machine linguistics and natural language processing tools. It can assist in understanding an individual's psyche by analyzing emotions expressed in online text [22]. Opinion mining and emotion mining are the two most common subcategories of sentiment analysis. Opinion mining includes subjectivity detection and polarity classification. Emotion detection, polarity classification, and emotion categorization are necessary processes of emotion mining. We will concentrate on opinion and emotion mining in this study. The taxonomy of sentiment analysis from text [22].

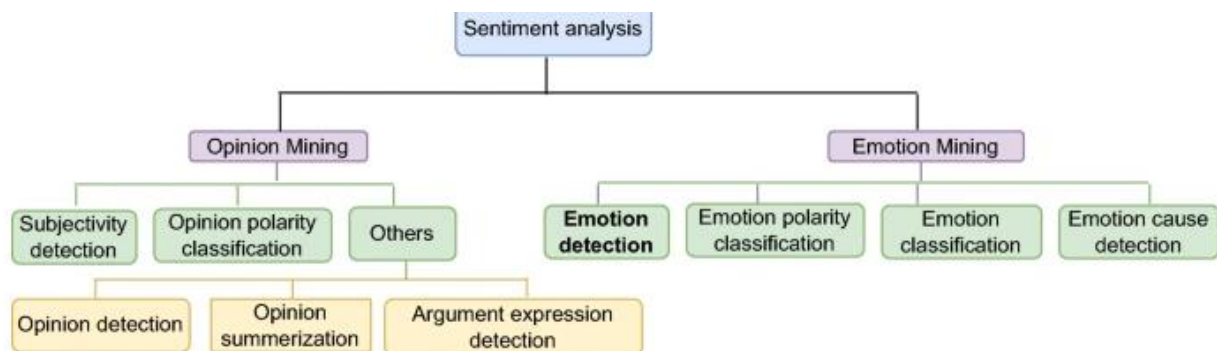


Figure 4 Taxonomy of sentiment analysis

Text sentiment analysis is one of the most important tasks in the field of public opinion monitoring, service evaluation, and satisfaction analysis in the current network environment. At present, the sentiment analysis algorithms with good effects are all based on statistical learning

methods. The performance of this method depends on the quality of feature extraction, while good feature engineering requires a high degree of expertise and is also time-consuming, laborious, and affords poor opportunities for mobility. Neural networks can reduce dependence on feature engineering. Recurrent neural networks can obtain context information but the order of words will lead to bias; the text analysis method based on Convolutional neural network can obtain important features of text through pooling but it is difficult to obtain contextual information. The basic task of sentiment analysis is to classify the polarity of a given text at the document, sentence, or feature/aspect level and to determine whether the opinions expressed in the document, sentence, or entity feature/aspect are positive, negative, or neutral.

2.7 Recurrent Neural Networks (RNN)

RNNs are a class of neural networks where connections between neurons form a directed cycle, allowing for feedback loops within the network. The main function of RNNs is to process sequential information based on internal memory captured by the directed cycles. Unlike traditional feedforward neural networks, RNNs can remember previous computations and reuse them for processing subsequent elements in a sequence of inputs. Recurrent neural networks [15] are a class of neural networks whose connections between neurons form a directed cycle, which creates feedback loops within the RNN. The main function of RNN is the processing of sequential information on the basis of the internal memory captured by the directed cycles. Unlike traditional neural networks, RNN can remember the previous computation of information and can reuse it by applying it to the next element in the sequence of inputs.

LSTM is a special type of RNN designed to overcome the vanishing gradient problem, which occurs when training traditional RNNs on long sequences. LSTM networks have memory cells with gates that control the flow of information, allowing them to retain long-term dependencies in the data. LSTM architecture includes input gates, forget gates, and output gates, which regulate the flow of information through the network. The LSTM layer consists of 200 memory cells, which process the sequential input data. A fully connected layer follows the LSTM layer, containing 128 cells for text classification. The final layer uses the sigmoid activation function to reduce the vector dimensionality from 128 to 1, as there are two classes to be predicted (positive and negative sentiment). long short-term memory (LSTM), which is capable of using long memory as the input of activation functions in the hidden layer [15]. Figure 5 illustrates an

example of the LSTM architecture. The input data is preprocessed to reshape data for the embedding matrix [15]. The next layer is the LSTM, which includes 200 cells. The final layer is a fully connected layer, which includes 128 cells for text classification. The last layer uses the sigmoid activation function to reduce the vector of height 128 to an output vector of one, given that there are two classes to be predicted (positive, negative).

Overall, this passage outlines the architecture and functionality of LSTM networks for processing sequential data, particularly in the context of text classification tasks such as sentiment analysis.

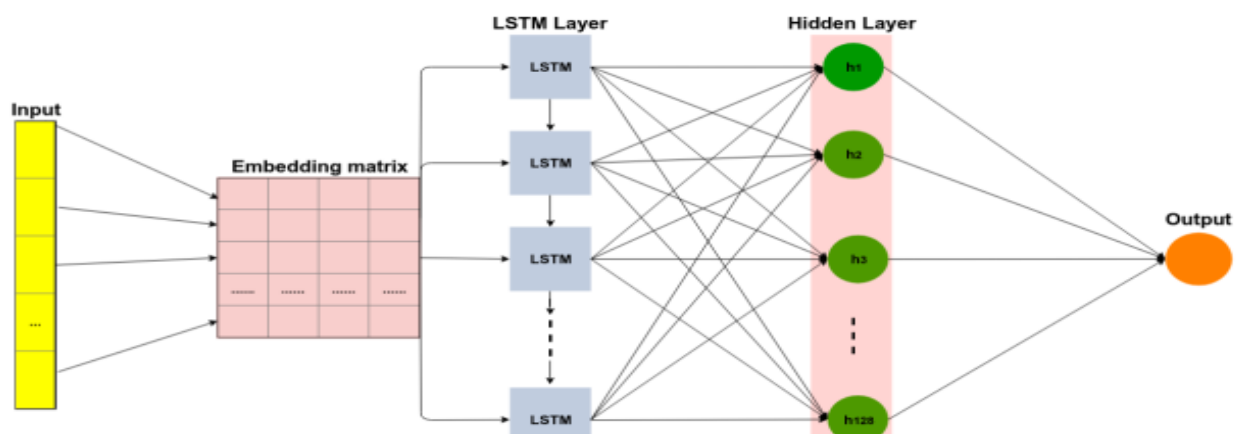


Figure 5 A long short-term memory network 1 LSTM, long short-term memory

RNN's perform very well for applications where sequential information is clearly important, because the meaning could be misinterpreted or the grammar could be incorrect if sequential information is not used. Applications include image captioning, language modeling and machine translation. RNN has two inputs, the present and the recent past, which is important because the sequence of data contains critical information about what is coming next, which is why RNN can do things other algorithms cannot [23]. A feed-forward neural network assigns, like all other deep learning algorithms, a weight matrix to its inputs and then produces the output. Note that RNNs apply weights to the current and the previous input. Furthermore, a recurrent neural network will also tweak the weights for both gradient descent and back propagation through time [23].

RNN category includes gated recurrent units (GRUs) and long short-term memory (LSTM) approaches. The main advantage of this technique is the ability to collect data or generate a data output from the prior knowledge. However, the disadvantage of this technique is that decision boundary might be overstrained when training set doesn't own samples that should be in a class. Overall, this technique is simpler than other techniques in the way of learning with high performance [24].

2.7.1 Recurrent Neural Networks and Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) networks are an extension of RNN that extend the memory. LSTM is used as the building block for the layers of RNN. LSTMs assign data “weights” which help RNNs to either let new information in, forget information, or give it important enough to affect the output [25]. The units of an LSTM are used as building units for the layers of an RNN, often called an LSTM network. LSTMs enable RNNs to remember inputs over a long period. This is because LSTMs contain information in a memory, much like the memory of a computer. The LSTM can read, write and delete information from its memory.

This memory can be seen as a gated cell, with gated meaning the cell decides whether to store or delete information (i.e. if it opens the gates or not), based on the importance it assigns to the information. The assigning of importance happens through weights, which are also learned by the algorithm. This simply means that it learns over time what information is important and what is not. In a long short-term memory cell, you have three gates: input, forget, and output gate. These gates determine whether to let new input in (input gate), delete the information because it is not important (forget gate), or let it affect the output at the current time step (output gate). LSTMs enable RNNs to remember inputs over extended periods by storing information in memory cells, similar to the memory of a computer. The LSTM's memory is managed through gated cells, which control whether information is stored or deleted based on its importance. The importance of information is determined by weights, which are learned by the algorithm over time. This allows the LSTM to adapt and prioritize relevant information.

LSTM cells contain three gates: input gate, forget gate, and output gate. The input gate controls whether new input information should be stored in memory. The forget gate decides whether existing information in memory should be forgotten because it is deemed unimportant. The output gate determines whether the information stored in memory should influence the output of

the current time step. Overall, LSTMs play a critical role in enhancing the memory capabilities of RNNs, allowing them to effectively capture and retain long-term dependencies in sequential data. By managing information flow through gated cells and weight assignments, LSTMs enable more sophisticated processing of sequential data in various applications, including natural language processing and time series analysis.

2.8 Sentiment Analysis

People express their idea and make a judgment about events around them whether they love, hates, support, criticize, or think negatively, positively, or neutrally. This kind of judgment is commonly known as sentiment [25]. The sentiment is a broad term that concerns people's judgment, attitudes, and appreciation of government, politics, products, places, events, etc. around the world. Whereas sentiment analysis concerns the use of technology and systematic techniques to categorize this sentiment from written languages into different categories like positive, negative, neutral, etc. [25] Defined the sentiment analysis as follows: "Sentiment analysis, also called opinion mining, is the field of study that analyzes people's opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes."

2.8.1 Techniques of sentiment Analysis

The overall approaches toward sentiment analysis are classified into two. The first and earliest one is a lexicon-based approach and the second one is a machine-learning approach. Techniques based on machine learning: In this type it is applied through extracting sentences and side levels. Features consist of Parts of Speech Marks (POS), n-gram, bi-gram, monogram and bag-of-words. Machine learning also has three aspects of sentence and side: Nave Bayes, Vector (SVM) and Maximum Entropy. and Lexicon-based technologies: In this type, they depend on trees through which decisions are made such as k-Nearest Neighborhood (K-NN), Conditional Random Field (CRF), Hidden Markov Model (HMM), and Class Dimensional Classification (SDC) and Chain Optimization (SMO) related to emotional classification methodologies.

The machine learning approach also has three categories: a) supervised; b) semi-supervised; and c) non-supervised. This approach is capable of automation and it can handle a large amount of data and therefore it is very suitable for the analysis of sentiment. In this section, many sentiment

analysis studies are discussed using deep learning techniques. This review is also done in the field of emotional analysis based on several recent studies [6].

2.9 Related Works

There are research works that were done internationally and locally on sentiment mining, aspect-based summarization in different languages like English, Arabic and Amharic using different techniques and approaches. Most approach to sentiment analysis follows either machine learning approach or lexicon-based approach. Machine learning approach can be classified into two such as Supervised (labeled data) and Unsupervised (no labeled data) learning. The Supervised approach can be rule-based classification, decision tree, linear classification and Probabilistic classifier. Lexicon based approach can be classified into two such as dictionary based and corpus-based approach (semantic and statistical).

There are not many studies on sentiment analysis for Afaan Oromoo, as it is a low-resource language that lacks standardized and sufficient corpora for natural language processing tasks. However, I found some papers in web search results that propose different deep learning architectures for sentiment analysis for Afaan Oromoo using Recursive neural network (RNN) and long short-term memory (LSTM) approach.

One of the papers is titled "Sentiment Analysis for Afaan Oromoo Using Recursive Neural Network and Long Short-Term Memory" [13]. This paper provides a detailed description of the proposed model and the data collection and annotation process. The [13] collected data from two domains, Facebook and Twitter, and manually annotated them into three classes: positive, very negative, negative, and neutral. They used character-level word embedding to represent the input text and trained the CNN-Bi-LSTM model on the prepared corpus. The authors [13] compared their model with other baseline models, such as CNN, Bi-LSTM, and SVM, and showed that their model outperformed them in both Facebook and Twitter datasets. They also discussed the challenges and limitations of their work, such as the lack of a standardized and sufficient amount of data set, the informality and misspelling of the text, and the subjectivity and ambiguity of the sentiment labels.

A third way is to use word embedding, which are numerical representations of words that capture their semantic and syntactic properties. Word embedding's can help reduce the dimensionality

and sparsely of the input data, and enable the deep learning models to learn more effectively from the words and their contexts. Word embeddings can be learned from scratch, or obtained from pre-trained models, such as Word2Vec, Glove, or BERT.

There are several deep learning architectures that can be used for Amharic sentiment analysis, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory networks (LSTMs), bidirectional LSTMs (Bi-LSTMs), and transformers.

Sentiment analysis is the task of identifying the emotional tone or attitude of a text, such as positive, negative, or neutral. It is a useful technique for understanding the opinions and feelings of people expressed in natural language. Sentiment analysis can be applied to various domains, such as social media, e-commerce, politics, healthcare, and entertainment.

One possible approach for Amharic sentiment analysis is to use deep learning, which is a branch of machine learning that uses neural networks to learn from data and perform complex tasks. Deep learning has achieved remarkable results in many NLP tasks, such as machine translation, text summarization, and text generation. However, deep learning also requires a large amount of data and computational resources, which may not be easily accessible for low-resource languages.

A third way is to use Word embeddings are numerical representations of words that encapsulate their semantic and syntactic properties. These embeddings help in reducing the dimensionality and sparsity of input data, which in turn enables deep learning models to learn more effectively from the words and their contexts. There are two primary approaches to obtaining word embeddings. *Learning from Scratch:* This approach involves training the word embeddings along with the deep learning model on the specific dataset of interest. This method ensures that the embeddings are tailored to the specific domain and context of the data, but it requires a substantial amount of data and computational resources.

Using Pre-trained Models: Pre-trained embeddings are generated from large corpora of text and can be used as a starting point for many natural language processing (NLP) tasks. Some of the most well-known pre-trained models include:

Word2Vec: Developed by Google, Word2Vec creates embeddings by predicting the context of words within a corpus using models like Continuous Bag of Words (CBOW) and Skip-gram.

GloVe (Global Vectors for Word Representation): Developed by Stanford, GloVe generates embeddings by analyzing the co-occurrence matrix of words in a corpus and learning the global statistical information of the words.

BERT (Bidirectional Encoder Representations from Transformers): Developed by Google, BERT is a transformer-based model that generates contextualized word embeddings by considering the entire sentence in which a word appears, thus capturing more nuanced meaning.

Using pre-trained models can save significant time and resources, and these embeddings often perform well on a variety of NLP tasks due to their extensive training on large and diverse datasets. However, for highly specific domains or unique vocabularies, fine-tuning pre-trained embeddings or training embeddings from scratch might still be necessary.

Researchers have extensively investigated sentiment analysis across various languages. These investigations typically employ techniques at different levels of analysis, such as:

Document-level: Analyzing sentiment of entire documents.

Sentence-level: Determining sentiment for individual sentences.

Aspect-based level: Focusing on sentiments related to specific aspects or entities within the text.

Focus on Afan Oromo Sentiment Analysis Specific studies have targeted Afan Oromo, a Cushitic language spoken by millions in Ethiopia, aiming to classify the emotional polarity (positive, negative, neutral) of sentences.

These studies typically utilized textual content for sentiment analysis, employing various machine learning and deep learning techniques to predict sentiment. However, they did not explore the impact of emojis on sentiment classification. Emojis often convey significant emotional context that can influence the sentiment of a text, but their role was neglected in these studies.

Related works to sentiment analysis for Afaan Oromoo sentence classification using deep learning approaches. This table will include details such as the title of the work, authors, year of publication, the deep learning approach used, and key findings or contributions.

Table 2 Summary of Reviewed Papers

Title	Authors	Year	Deep Learning Approach	Key Findings/Contributions
Sentiment Analysis for Afaan Oromoo using Deep Learning	Megersa Oljira, Bayisa Natea Sima	2021	CNN, LSTM	Achieved 85% accuracy, demonstrated the effectiveness of CNN-LSTM hybrid model for Afaan Oromoo.
Sentiment Classification in Low-Resource Languages	Sufian Kedir Abdella, Worku Jifara Sori	2020	BERT, Transfer Learning	Showed that transfer learning with BERT significantly improves performance for low-resource languages like Afaan Oromoo.
Neural Networks for Afaan Oromoo Sentiment Analysis	Megersa Oljira Rase	2019	RNN, LSTM	Used RNN and LSTM to achieve state-of-the-art results for sentiment analysis in Afaan Oromoo.
Multilingual Sentiment Analysis with Deep Learning	Koena Ronny Mabokela Turgay Celik	2022	Multilingual BERT	Demonstrated the feasibility of using multilingual models for sentiment analysis across different languages, including Afaan Oromoo.
Text-based sentiment analysis using machine learning and deep learning	Wayessa and Abas	2020	supervised machine learning approaches	Document-level and Sentence-level

Research Openings: Incorporation of Emojis is none of the reviewed studies considered how emojis within texts might affect sentiment analysis. This is a significant gap because emojis can add nuanced emotional context that purely textual analysis might miss and Performance

Measures is the impact of emojis on the accuracy and reliability of sentiment classification models remains unexplored and model Training is Developing models that can interpret and factor in the emotional context provided by emojis and Performance Evaluation is Assessing the impact of emojis on model performance to ensure more nuanced sentiment predictions. Sentiment analysis in low-resource languages like Afaan Oromoo and Amharic requires innovative approaches due to the shortage of data and tools. Techniques such as deep learning, data augmentation, transfer learning, and word embeddings are crucial. The research on AO shows promising results using advanced neural network architectures despite the challenges. One significant gap identified in the reviewed literature is the lack of consideration of emojis in sentiment analysis for Afaan Oromoo.

Using RNN and LSTM models to analyze the role of emojis in text can uncover the hidden meanings behind their usage. By capturing the sequence and context in which emojis appear, these models can provide insights into how emojis contribute to sentiment and meaning, enhancing the overall understanding of social media communication. This is a significant gap because emojis can add nuanced emotional context that purely textual analysis might miss and Performance Measures is the impact of emojis on the accuracy.

Chapter Three

3. Designing Sentence Level Sentiment Analysis

3.1. Materials and Methods

3.1.1. Data collection

The primary data source is the Oromia Broadcasting Network's Facebook, Twitter, and YouTube pages. These platforms are chosen due to the significant quantity of user-generated opinions, particularly related to government policies and socio-political issues.

Reasons for Choosing Oromia Broadcasting Network's Pages: The Oromia Broadcasting Network's pages provide a wealth of genuine and reliable user-generated data, especially regarding government policies and related socio-political issues. Being a government organization's page, it ensures a diverse range of opinions, including both supportive and critical viewpoints. The pages are public, allowing people to freely express their opinions about government-related matters [8].

The data collection process resulted in a total of 1,552 positive and 1,248 negative reviews. The collected data is saved in comma-delimited (CSV) format in Excel for further processing and analysis. (<https://exportcomments.com/>) The collected data includes articles with headlines and descriptions of news items. Initially in Word files, the data is converted into Excel format (.csv) to facilitate preprocessing. Google Colab is utilized as a comprehensive tool for designing, implementing, and testing Afaan Oromoo sentence classification models. Various operations such as data preprocessing, embedding, and classification are performed using Google Colab. The libraries employed include Kaggle, Jupiter Notebook, TensorFlow deep learning library, Kera's deep learning library, and Genism library.

Importance of Dataset: In Natural Language Processing (NLP), the quality of the dataset plays a crucial role in the success or failure of research endeavors.

Having labeled data significantly impacts the effectiveness of sentiment analysis models.

The collected data undergoes preprocessing and feature extraction before being used for sentiment classification.

This section provides insights into the data collection process and the tools utilized for designing and implementing the sentiment analysis system. Subsequent sections will delve into dataset preparation, preprocessing, feature extraction, and classification methodologies.

3.1.2. Data preprocessing

Data preprocessing step is one of the basic important tasks before proceeding with the model building part. To avoid the catastrophic move towards data building part, having clean data that is free of falsification and ambiguities is very important. Therefore, all the unwanted symbols, characters, etc. that do not affect the objective of the summarization are dropped. The following important preprocessing tasks were performed for the desired results.

In cleaning the data process apostrophe plays an important role in reading and writing system the Afan Oromo language. There are times when the apostrophe is used interchangeable with the spelling “h”. For instance, “ka’e”, “ba’aa”

The deep learning method requires the labeled dataset for training purposes the dataset collected was labeled manually by experts. After that, the data is split into training and testing data using scikit-learn train-test-split. The training data used to train the classifiers, and the test data used for testing the accuracy of the classifiers.

The 80/20 split provides a good balance, giving the model sufficient data to train on (80%) while keeping enough data (20%) to test its generalization ability. The `train_test_split` method from the sklearn library is straightforward to use, making it a practical choice for quickly dividing datasets. It abstracts away the complexities involved in splitting data and ensures that the process is done correctly. The method is optimized for performance, allowing for fast splitting of even large datasets. This efficiency is crucial in machine learning pipelines where quick iteration and validation are necessary.

Another step is preprocessing to exclude irrelevant data from the dataset. Preprocessing is very important as it reduces the computational time and increases the classifier performance because noisy data can slow the learning process and decrease the efficiency of the system. Accordingly,

our preprocessing includes the following: Cleaning: Removal of user names, Removal of links, lower casing, Removal of non-Afaan Oromo texts, unnecessary characters, etc.

Stop word removal: some Afaan Oromo Stop words are significant for sentiment classification and need to remain in the text. For instance, the “hin” is used to indicate the negativity of the word: for example, “dhufeera”, “hin dhufne”. In another case, some stop words constitute a phrase: “walii hin gaallu”, “isin waliin jirra” etc. These stop words portray important information. So, we filtered removed stop words through a manual process that is not relevant for the classification process.

Normalization: homophones like “baay’ee” and “baayyee” has the same meaning with different writing. The only difference is that the apostrophe (’) is replaced by “y”. Normalization of elongated texts, for example, “sin jaallannaaaaaa” is normalized to “sin jaallanna”.

Normalization of numbers into equivalent texts. Example: “sin jaallanna 100%” normalized to “sin jaallanna persentii dhibba tokko”.

Spelling correction: we encounter many wrongly spelled texts. So, they need to be corrected to the right spelling.

RNNs are probably the most commonly used deep learning models for NLP, and with good reason. Because these networks are recurrent, they are ideal for working with sequential data such as text. In sentiment analysis, they can be used to repeatedly predict the sentiment as each token in a piece of text is ingested."

3.1.3. Tokenization

Tokenization is the process of splitting an input sequence into tokens. It a useful unit for semantic processing. The tokens usually consist of either a single word or what is called an N-gram, meaning that N consecutive words are split into a single token. The idea is to preserve some of the information that is stored in the order of the words.

3.1.4. Stemming

Stemming is a crucial preprocessing step in natural language processing (NLP) that reduces words to their base or root form by removing inflections and derivational forms. This process is particularly important in morphologically rich languages like Afaan Oromo, where words can

have many different forms based on tense, case, mood, and other grammatical features. In Afaan Oromo, words can take on many forms due to rich inflectional and derivational morphology. For example, the word "biyya" (country) can appear as "biyyoota" (countries), "biyyatti" (to the country), etc. By reducing these variants to a single root form, stemming [27].

3.1.5. Feature Selection

After preprocessing is completed, the next step is featurizing extraction which is used for training the classifiers. Features are the piece of information taken from the text and given to the algorithm for classification. Feature selection is not used only for dimension reduction of our data, but also it is crucial for making training faster and it can improve accuracy by removing features that are noisy and irrelevant for classification. In addition, feature selection can help to avoid over fitting. In sentiment analysis, features can be words, terms or phrases that strongly express the opinion as negative or positive.

There are several methods that are used to select the most important features in a text. Among this one of the common and effective ways to select features is to assign weights to them and then define a certain threshold for the targeted features. TF-IDF feature selection was investigated for the [28] feature selection is a simple and effective feature selection paradigm. It is easy to remove hundreds of rare and uninformative features. In TF-IDF weighting the importance of features is computed based on both term frequency and inverse document frequency.

TF-IDF which stands for Term Frequency Inverse Document Frequency and it is a statistical method of evaluating the significance of word in given documents. Term frequency (tf): measures the frequency of the occurrences of a given term in a document. Inverse document frequency: measures the cost of the word in the document, i.e. if the word is common or infrequent in the entire document. The main idea behind tf-idf follows that the terms that appear frequently in a document are less important than terms that are infrequent or rare. The TF-IDF customs the vector space modeling system for text document representation.

TF-IDF measure accounts both, the Term Frequency and the Inverse Document Frequency. The term frequency indicated as (t, d) is the total number of times a given term t appears in document d against the total number of all words in the document. If the frequency of a given term

increases in a document, then its tf also increases. The inverse document frequency represented as (t, D) is a measure of how much information the word provides. In another word, it measures the worth weight of a given word in a given document. IDF shows how common or rare a given word is across all documents.

Term frequency–Inverse document frequency is the product of term frequency $tf(t, d)$ and inverse document frequency (t, D) . TF-IDF can be computed as: $(t, d) = \text{number of times term } (t) \text{ in document } (d) \text{ total number of terms } (t) \text{ in document } (d)$. The Inverse Document Frequency measures how word contribute to discriminate each document. In most literature, single words were used as features. If the term “Amaan xalayaa barreessaa jira garuu maxxansuu dagate” (“Aman is writing a letter but forgot to post”) occurs in a sentence, it is likely to have a negative sentiment. However, considering only single sentence as a feature have several limitations. For example, Negations, such as “gadhee miti” (“not bad”) or (gaarii miti) “not good” for example, will not be taken into account. So, this leads to misclassification as a sentence feature can even change the direction of the classification.

Negations are used in order to contradict or deny a statement. Commonly used Afaan Oromoo negations are introduced with ‘hin’ and ‘miti’. An example with a sentiment bearing verb: "inni ni danda'a" (“(he can)”) "inni hin danda'u" (he cannot) An example with a sentiment bearing adverb: "kun gaariidha" (this is good) "kun gaarii miti" (this is not good).

So, in this thesis, we used RNN as features to overcome this problem. In another case, Phrasal verbs are common in the Afaan Oromoo language. They are verbs which are composed of one verb in combination with one or more particles, for example, "waa'ee saa walii hin gallu" (we disagree about it). Each part needs to be taken into account for the expression to make sense. To overcome such problems, we used n-grams as features.

For both selected deep learning algorithms, we used word embedding as a feature. One of the important features of Word embedding is that it provides a dense representation of words and their relative meanings. The word embeddings are very important in sentiment analysis of social media texts where social media posts are usually very short, there’s a lack of features for effective classification. Thus, word embedding models can be used to learn different word usages in various contexts. To detect the sentiment polarity from short texts, we need to explore

deeper semantics of words using deep learning methods. As addressed by the researcher [29], there is an issue in the polarity of opinion in their study. That means people express their opinion in a context-based or/and indirect manner. They may use positive words to express their negative feeling or vice versa. Thus, it needs further research to make the system consider context-based or semantic opinion mining. So, to improve this problem we choose the word embedding in this study.

Word embedding is an improvement over sparse representations used in a traditional bag of word model representations. In this work Embedding layer is initialized with random weights and will learn an embedding for all of the words in the training dataset (i.e. the network learns a word embedding while fitting or while training a neural network by its own). For Afaan Oromoo language there are no such resources. RNN uses filters or kernels to detect features. Recursive is one of the main principal components of RNN. The term Recursive signifies the mathematical combination of two functions to yield a third function. It combines two sets of information and produces another information. So Recursive is applied to the input data with the help of a filter or kernel and then produce a feature map. Accordingly, in this thesis, we conducted our experiment with different filters (1, 2, 3, 4, and 5) size with 64 filters.

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thesis, we used RNN as features to overcome this problem. Phrasal verbs are common in the Afaan Oromoo language, and they consist of one verb in combination with one or more particles. Each part needs to be taken into account for the expression to make sense. To address such problems, we used n-grams as features.

For both selected deep learning algorithms, we used word embedding as a feature. Word embedding provides a dense representation of words and their relative meanings, making it essential for sentiment analysis of social media texts where posts are usually very short. It helps to explore deeper semantics of words using deep learning methods. There is an issue in the polarity of opinion in previous studies, as people express their opinions in a context-based or indirect manner. They may use positive words to express their negative feelings or vice versa. Thus, further research is needed to consider context-based or semantic opinion mining. To improve this problem, we chose word embedding in this study.

Word embeddings are an improvement over sparse representations used in traditional bag-of-words model representations. The embedding layer is initialized with random weights and learns an embedding for all words in the training dataset while training a neural network.

3.2. Feature Extraction and Classification

Feature extraction is the process of identifying distinguishing features from either an input image or text. Once an input text is converted into integer representation and padded into fixed sized vectors using the word-embedding technique, the next step is extracting distinguishing features needed to uniquely identify each text. Relevant local features are extracted from the input Sentences by using a series of Recursive available in a recursive neural network.

Input: - Afaan Oromoo Sentences

step1: load tokens

Step 2: load a file that contains a list of characters and Sentences

Step 3: for each character and Sentences=>check

Step 4: if a character or word gets from a list

Step 5: change each character and word into standard form

Output: - normalized Afaan Oromoo tokens

Recurrent Neural Networks like LSTM and GRU are good at capturing long-range dependencies between input text and contextual information. This step consists of inputs obtained from the embedding layer. It consists of three convolution layers, one dropout layer, and an activation layer. The convolution layer consists of a sequence of convolutional filters used to capture the important local features that represent an input and a convolutional kernel used to scan the useful features from the input.

Generally, to attain the above-mentioned objective, the following methodology will be implemented:

- Fetching the data by using the APIs available.
- After fetching the data, firstly the Data Pre-processing is done, where we are doing the following: converting the data into lowercase, Drop Non alphabets, Drop URLs, drop Stop words, Lemmatization of words, drop unwanted words to remove noise, and Parts of Speech (POS) tagging. Secondly, feature extraction is done where we extract the most important sentiment features through various feature models.
- Now we combine all above feature set model by using any deep learning algorithm (let's say by RNN).
- New feature set is present which is feed into the Neural network where our data is trained by Back Propagation neural network validate by fold cross validation method, and test by feed forward neural network. Validation is done as it ensures that our data is not over fitting.
- Now, we predict the output (with the help of test data) as positive, neutral & negative.
- At last we are checking the performance of our result with the help of computational accuracy, Recall, Precision, F1 Score.

RNNs are neural networks that can process sequential data, such as text, audio, or time series data. They contain a “hidden state” that is passed from one element in the sequence to the next, allowing the network to remember information from previous elements.

At each time step, the RNN takes in an input and the current hidden state, and produces an output and a new hidden state.

The output and new hidden state are used as input for the next time step, and this process continues until the entire sequence has been processed. RNNs are well-suited for tasks involving variable-length sequences and maintaining state across elements.

Preprocessing the data, including converting it into lowercase, dropping non-alphabetic characters, URLs, stop words, and lemmatizing words, and performing parts of speech (POS) tagging. Feature extraction to extract the most important sentiment features through various feature models. Combining all feature set models using any deep learning algorithm (e.g., RNN). Training the data using Back Propagation neural network validated by fold cross-validation method and testing using feed-forward neural network. Validation ensures that the data is not overfitting. Predicting the output (positive, neutral, or negative) using the test data. Evaluating the performance of the result using computational accuracy, recall, precision, and F1 score. RNNs are neural networks capable of processing sequential data, such as text, audio, or time series data. They contain a "hidden state" passed from one element in the sequence to the next, enabling the network to remember information from previous elements. At each time step, the RNN takes in an input and the current hidden state, producing an output and a new hidden state. This process continues until the entire sequence has been processed. RNNs are well-suited for tasks involving variable-length sequences and maintaining state across elements.

3.3. RNN

Artificial Neural Networks (ANNs), inspired by the human brain, aim to teach computers to process data. This involves a machine learning process (deep learning) which uses interconnected nodes, or neurons, in a hierarchical structure similar to the human brain. It creates an adaptive system that computers use to learn from mistakes and constantly improve. As a result, ANNs attempt to solve complex problems, such as summarizing documents or recognizing faces, with greater precision.

A RNN is a special type of ANN (Artificial Neural Network) adapted to work for time series data or data that involves sequences. It is trained to process and convert a sequential data input into a specific sequential data output. Sequential data is data such as words, sentences, time-series data where sequential components interrelate based on complex semantic and syntax rules [30].

Unfolding a Recurrent Neural Network

A simple RNN has a feedback loop, as shown in the figure below. The feedback loop shown in the grey rectangle can be unrolled in three-time steps to produce the second network below. We can also vary the architecture so that the network unrolls k -time steps.

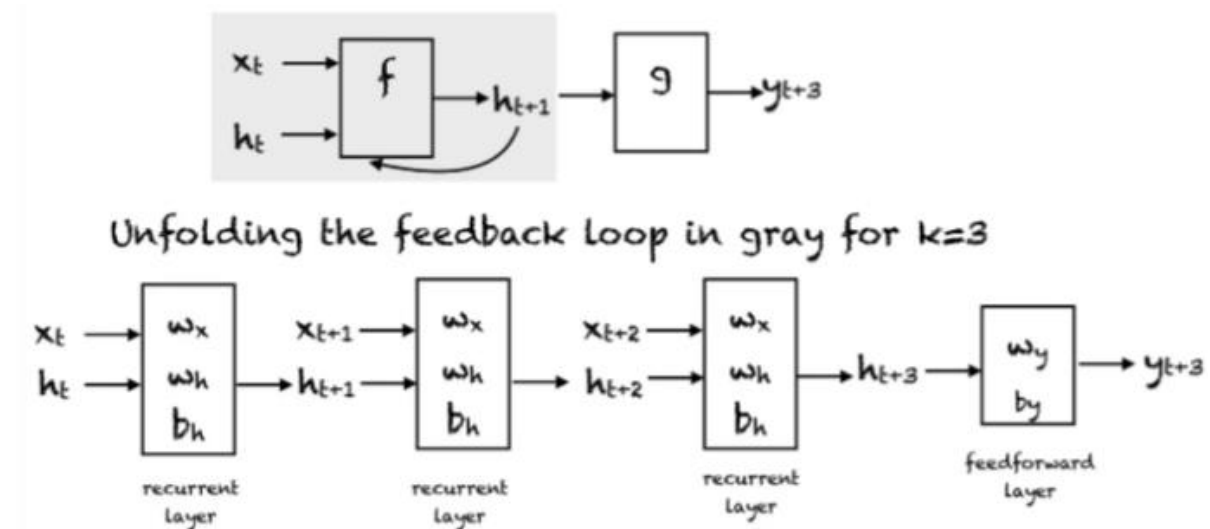


Figure 6 Compressed representation (top), unfolded network (bottom). Image from: RNN Introduction

At every time step, we can unfold the network for k time steps to get the output at time $k+1$. The unfolded network is similar to the feedforward neural network. In the feedforward pass of an RNN, the network computes the values of the hidden units and the output after k -time steps. The weights associated with the network are shared temporally. Each recurrent layer has two sets of weights: one for the input and the second for the hidden unit. The last feedforward layer, which computes the final output for the k th time step, is just like an ordinary layer of a traditional feedforward network [26].

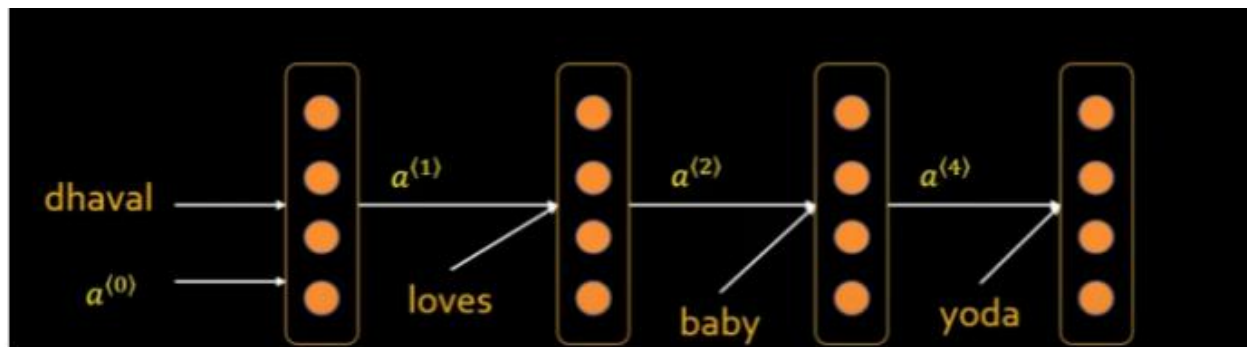


Figure 7 An Example of RNN. Image from: <https://www.youtube.com/watch?v=Y2wflKQyd1I&t=526s>

These are four single layers but show the status of different time steps. Supply the output of the previous work as an input to the second word to generate text in sequence. RNNs are made of neurons which are data-processing nodes that work together to perform complex tasks. There are typically four layers in RNN, the input layer, output layer, hidden layer, and loss layer. The input layer receives information to process, the output layer provides the result. Positioned between the input and output layers, the hidden layer can remember and use previous inputs for future predictions based on the stored memory. The iterative processing unfolds as sequential data traverses through hidden layers, with each step bringing about incremental insights and computations [26].

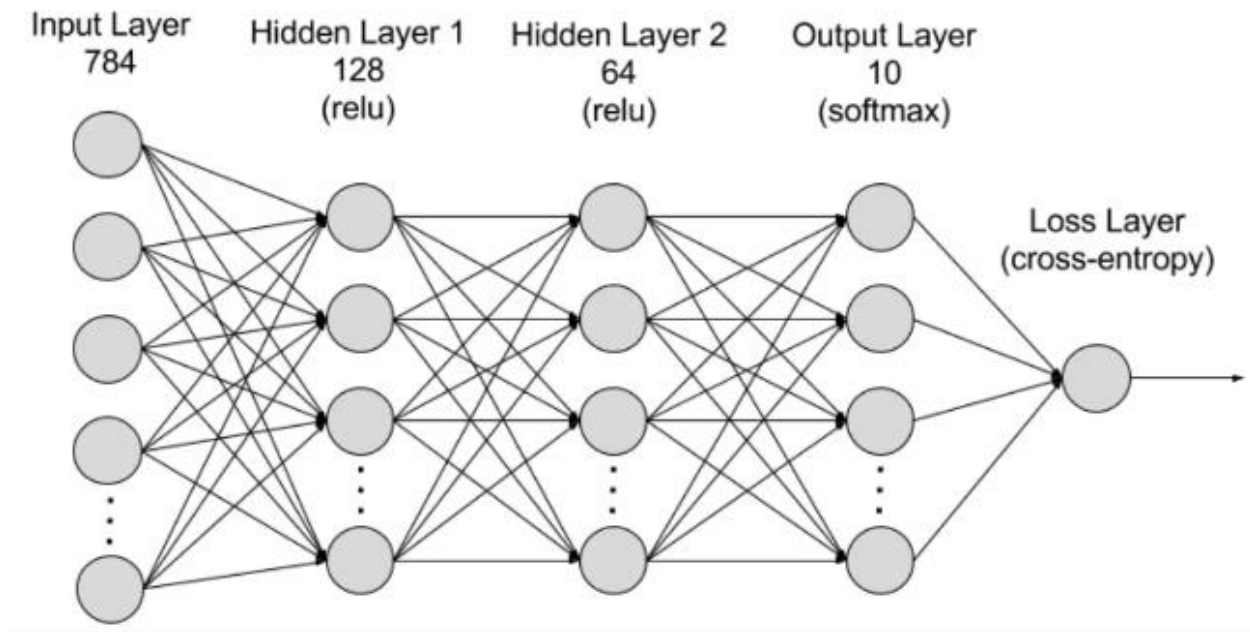


Figure 8 RNN network. Image from: <https://aws.amazon.com/what-is/recurrent-neural-network>

Activation functions determine whether a neuron should be activated or not by calculating the weighted sum and further adding bias to it. It can introduce non-linearity that typically converts the output of a neuron to a value between 0 and 1 or -1 and 1. Common activation functions that can be used are: The sigmoid function, Tanh function & ReLu function

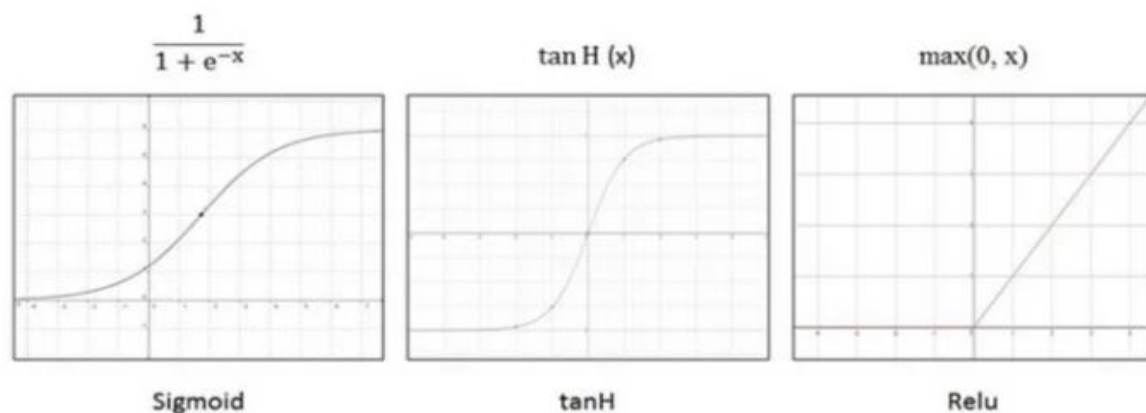


Figure 9 Activation functions. Image from Kazi, activation function

Training a Recurrent Neural Network

RNNs are trained by feeding with training data and refining their performance. Neurons have weights that are used to signal the importance of information when predicting the result during training. Weights are adjusted to improve prediction accuracy. A method called backpropagation through time (BPTT) can calculate model error and adjust weight relatively. BPTT moves from right to left through the graph that rolls back output to the previous time step and recalculates the error rate to identify which hidden state is causing errors and adjusts this weight to reduce the error, therefore improving prediction accuracy.

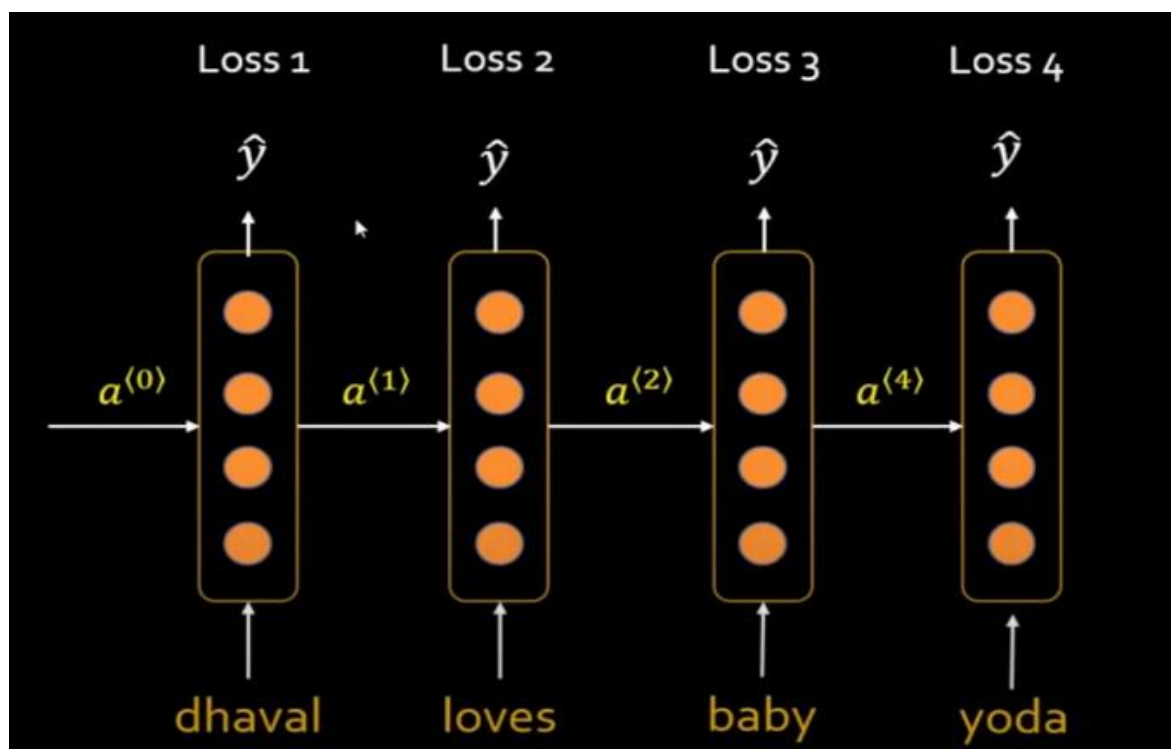


Figure 10 Training RNN. Image from: What is Recurrent Neural Network (RNN)? code basics

The general steps are as follows:

- ❖ Initialize the parameters of the neural network such as weight matrices (U, V, W) and bias vectors (b, c).
- ❖ Forward propagation to compute predictions. This involves computing the output of each layer in the network sequentially, using the current parameter values.

- ❖ Compute the loss to measure the difference between the predicted output and the actual target value.
- ❖ Back-propagation to compute gradients of the loss function. This involves propagating the error backward layer by layer through the network and using the calculus chain rule to calculate the gradients.
- ❖ Following gradient computation, adjust weights and biases using optimization methods like SGD or Adam to minimize the loss function.
- ❖ Repeat steps 2–5 until the criterion is met.

3.3.1. Long-Short-Term Memory Network (LSTM)

Long-Short Term Memory Network is a special kind of RNN, which can handle long-term dependencies of sequential data to overcome issues with the RNN architecture. LSTM is dominant compared to traditional statistical machine learning approaches for sentiment analysis as well as other NLP tasks. Due to the architectural changes, the error propagated through time will not vanish and the inputs received a long time ago will still play a major role despite the time when the input is received. Still, the sequential information flow guides to less performance when long sentences are fed to the LSTM network even though it allows processing sequential data preserving long-term dependencies [31].

3.3.1.1 Bidirectional LSTM (BiLSTM)

BiLSTM is an improvement to the LSTM architecture, where the model is trained on both positive and negative time directions. It has two parallel layers propagating in both directions. The output of BiLSTM is the concatenation of these two layers. For most tasks, BiLSTM learns faster than one-directional LSTM networks.

3.3.1.2 Stacked BiLSTM

Stacked BiLSTM consists of multiple layers which are stacked upon one another where hidden vectors of the lower layer are used as inputs to the upper layer. Many researchers have shown that the Performance of stacked BiLSTM model is higher than the performance of BiLSTM for both regression and classification tasks. Stacked Bi-LSTM is the base model for S-LSTM.

3.3.1.3 Sentence State LSTM (S-LSTM)

Sentence state LSTM (S-SLTM) is a state-of-the-art neural network for sentiment analysis which consists of a parallel state for each word. Not like traditional LSTM, it does not read the input sequence of words incrementally. Rather it uses recurrent steps to perform local and global information exchange between words simultaneously.

Precisely, S-LSTM represents the hidden states of all words simultaneously in each recurrent time step rather than processing words sequentially. In each recurrent time step, a given sentence state is represented using sub-states h^t of each word of the sentence and an overall sentence-level state g^t considering the sentence. States are updated recurrently by exchanging information between the states in each recurrent step to capture local and global information. The information exchange is conducted between consecutive words in a sentence and the overall sentence-level state.

S-LSTM uses recurrent information exchange between sub-states which incrementally improve the representation of the states in the given context.

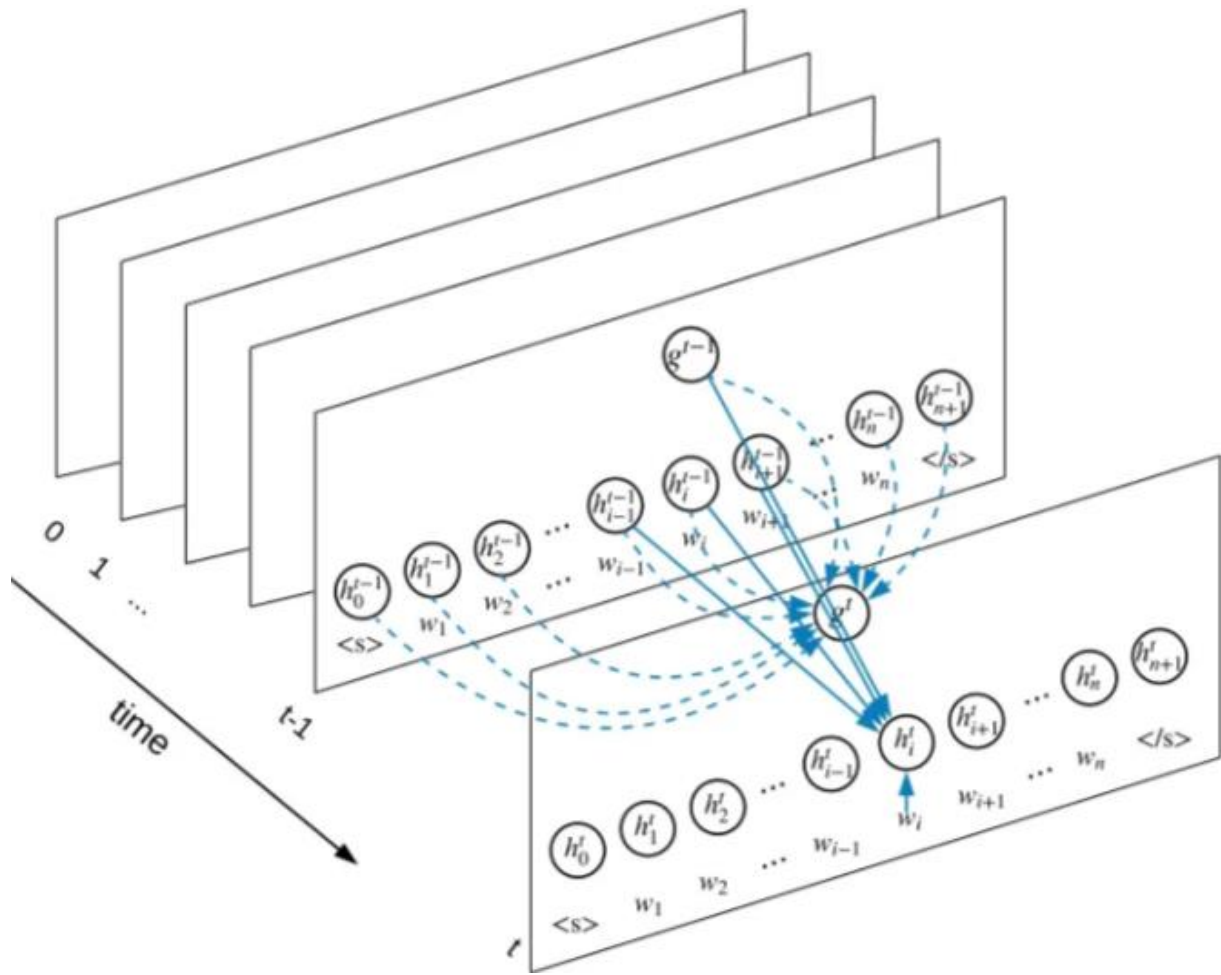


Figure 11 S-LSTM Architecture

$S = w_1, w_2, \dots, w_n$ # Input sentence
 h^t_i : Word-level sub-state for word w_i
 g^t : Sentence-level sub-state

H^t is the representation of S-LSTM state at a given time step t which includes all sub-states of the words and the overall sentence level state of a given sentence.

$$H^t = \langle h^t_0, h^t_1, h^t_2, \dots, h^t_n, g^t \rangle$$

S-LSTM state transition from a given time step to next time step consists of two transitions, Word-level sub-state transition from the given time step to next time step.

A sentence-level state transition from the given time step to next time step. The value of each hidden state is calculated based on the values of the current input, hidden states of the context window and sentence level state in the previous time step, together with their corresponding cell values.

The gated architecture of the proposed model controls the information flow from the context cells and input at a given time step.

S-LSTM architecture allows bidirectional information transfer between each and every word while the sentence level and word level states follow the same strategy to capture deeper context level information.

The main instinct of the LSTM network is that it has the mechanism of long-term memory and consequently is proficient in handling long-term dependencies. LSTM has a special structure called cell blocks. These cells are composed of an input gate, the forget gate and the output gate.

3.4 Transformers

Transformer Models are a type of deep learning architecture that relies on self-attention mechanisms to process sequential data, which allows them to capture long-range dependencies more effectively than traditional RNNs.

BERT (Bidirectional Encoder Representations from Transformers) is a transformer-based model designed for NLP tasks. It reads text bidirectionally, meaning it considers the context from both directions (left-to-right and right-to-left) for better understanding and generating contextual embeddings.

“The Transformer is the first transduction model relying entirely on self-attention to compute representations of its input and output without using sequence-aligned RNNs or convolution.”

“Transduction” means the conversion of input sequences into output sequences. The idea behind Transformer is to handle the dependencies between input and output with attention and recurrence completely.

The Transformer model, with its encoder-decoder structure and self-attention mechanisms, provides a powerful approach for handling sequential data. By leveraging pre-trained models like BERT and fine-tuning them on specific datasets, we can achieve high-performance sentiment analysis for Afaan Oromoo sentence classification. The autoregressive nature of the decoder in the Transformer ensures that each token is generated in the correct order, maintaining the context and dependencies within the sequence.

The RNNs (LSTM, GRU) have a recurrent underlying structure and are, by definition recurrent. It is then hard to parallelize the learning process because of this fundamental property. To overcome this issue, [32] a new architecture solely based on the attention layers; the Transformer. It has the advantage to catch the long-range dependencies of a sentence and to be parallelizable.

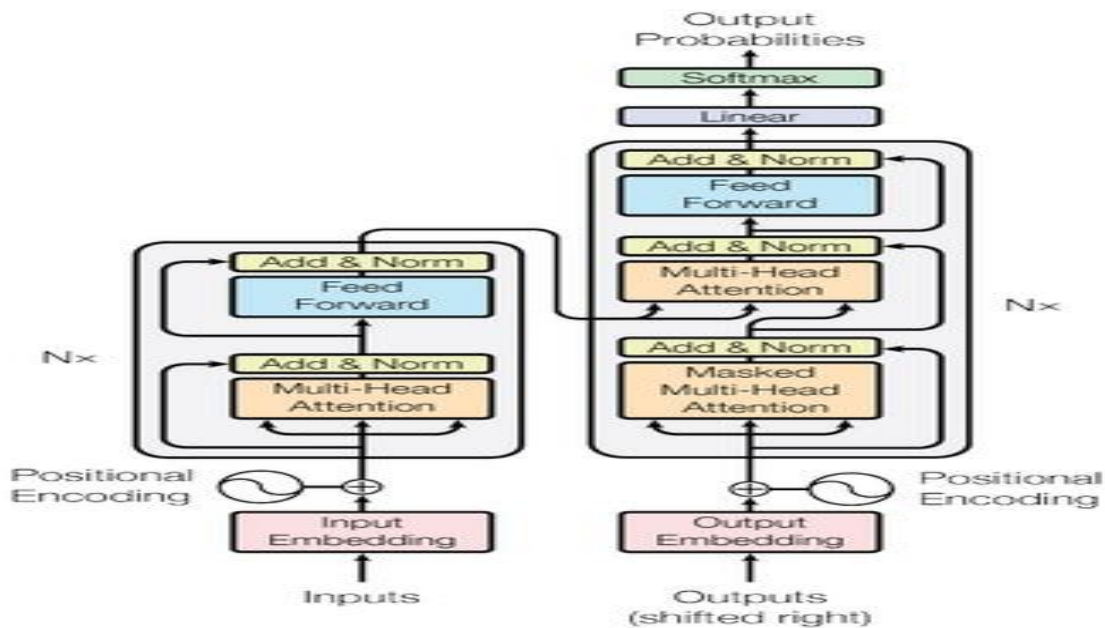
3.4.1 Transformer architecture

Encoder consists of a stack of identical layers, each containing two main components: Self-Attention Mechanism: This allows the model to focus on different parts of the input sequence when encoding a particular token and Feed-Forward Neural Network: This is a fully connected

network applied to each position separately and identically. The output of the encoder is a sequence of continuous representations, $Z = (z_1, \dots, z_N)$ $Z = (z_1, \dots, z_N)$ $Z = (z_1, \dots, z_N)$.

Decoder also consists of a stack of identical layers, but with an additional attention mechanism that allows it to attend to the encoder's output: Self-Attention Mechanism: Similar to the encoder, but it only attends to the positions up to the current token for autoregressive generation. Encoder-Decoder Attention: This mechanism allows the decoder to focus on relevant parts of the input sequence as it generates each token in the output sequence. Feed-Forward Neural Network: As in the encoder, this is applied to each position. The decoder generates the output sequence $Y = (y_1, \dots, y_M)$ $Y = (y_1, \dots, y_M)$ $Y = (y_1, \dots, y_M)$ autoregressively, meaning it produces one token at a time, using the previously generated tokens as additional context [32].

Table 3 The architecture of the Transformer



Transformers over LSTM and seq2seq models can be attributed to several factors:

Handling Long-Range Dependencies: Transformers can capture relationships between words in a sentence, regardless of their distance, more effectively than RNNs and LSTMs. The self-attention mechanism allows for parallel processing of input sequences, leading to faster training times and the ability to handle larger datasets. Transformers are highly scalable, enabling the development of large-scale pre-trained models that can be fine-tuned for various tasks. The

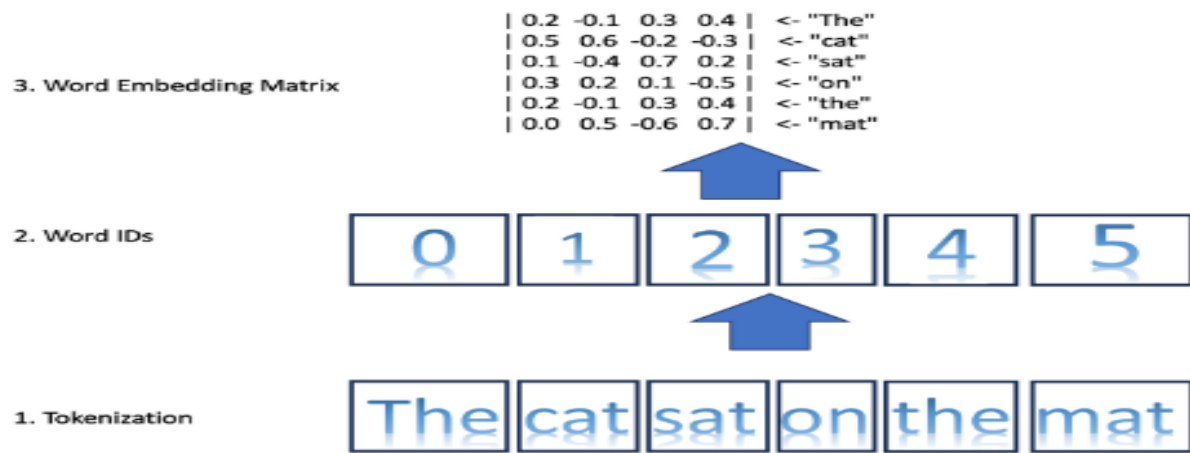
transformer architecture can be adapted for a wide range of NLP tasks, from text generation to language understanding. As a all, transformers have fundamentally changed the landscape of natural language processing. Their ability to efficiently process sequential data, handle long-range dependencies, and scale to large datasets has established them as the go-to architecture for NLP tasks. As research continues, we can expect further innovations and refinements in transformer models, solidifying their position as a cornerstone of modern NLP.

Transformerbased networks have changed the face of NLP tasks. They can go far beyond the results obtained with RNNs, and they can do it faster. They have helped solve many problems at the same time by providing a direct and efficient way to combine several downstream tasks. Nevertheless, much work remains before having a system with a human-level comprehension of the underlying meaning of texts, that is also sufficiently small to run on devices with low computational power.

3.5 Word Embedding

Words are map into vectors using word embedding models, Word embedding is a collection of statistical language modelling and techniques in NLP area. It maps words and phrase to vectors of real numbers; they capture both semantic and syntactic information of words [33]. Word embedding can be used to calculate word similarity which can be used in many tasks such as information retrieval. There are 4 ways are used for word embeddings which are word2vec, doc2vec, tfidf and embedding layer.

Table 4 Here's a detailed explanation of how word embedding works for the sentence "The cat sat on the mat":



Tokenization: First, we split the sentence into individual words or tokens: ["The", "cat", "sat", "on", "the", "mat"].

Word IDs: Each unique word in our vocabulary is assigned a unique ID. For simplicity, let's say our vocabulary only consists of the words in our sentence. We might assign the IDs as follows: "The" = 0, "cat" = 1, "sat" = 2, "on" = 3, "the" = 4 (note that "the" appears twice but has a different ID), "mat" = 5. In another way, you can think of this as one-hot-encoder

Word Embedding Matrix: We have a pre-trained word embedding matrix where each row corresponds to a word's embedding. The number of columns in this matrix is the dimension of the embedding space (let's say 4 for simplicity). It might look something like this:

Word2vec

Word2vec is NLP technology which takes a text corpus as input and words are represented as vectors. The proximity in vector space indicates semantic or functional similarity. The resulting word vector file can be used as features in many natural language processing and machine learning applications.

Doc2vec

Doc2vec model changes text document to numeric representations. Each sample is one vector, the dimension of the vector can be determined by user. Both word2vec and Doc2vec are

unsupervised learning methods and Doc2vec was developed on the base of Word2vec. Doc2vec inherits the advantages of word2vec such as take semantic and word order into consideration. The corpus is the collection of all the samples. Doc2vec method uses the corpus to train the model and use this model to map every sample to a fixed dimension vector. We set the dimension of text to be 300, then no matter how long the text is, the output is a 300-dimension numeric vector. The same corpus is used for word2vec method, after generating the word2vec model, every word will be mapped to a 100-dimension vector.

Tfi-df

Deep learning models need word embedding as an input variable in NLP. Word embedding is the process language modeling that converts texts into real numbers. In word embedding technique, each word is represented using dimension. Word2Vec is the prediction model which computes word embeddings from sentences. It includes CBOW (Continuous Bag of words) model and Skip- Gram model for feature learning.

3.6. Development tools

n this study, we utilized various development tools, including the Google Colab framework and deep learning frameworks, specifically TensorFlow.

We prioritized Google Colab because it is a free and open-source distribution of Python and other programming languages designed for scientific computing. Google Colab simplifies package management and development, enabling seamless integration with numerous open-source packages and libraries. This platform allows us to manage multiple data environments efficiently, ensuring they can be maintained and run independently without interference.

Google Colab offers a straightforward and robust environment, supporting the natural expression of procedural code, modularity, dynamic data types, and the ability to embed within applications as a scripting interface. For our implementation, we utilized Keras with the TensorFlow backend library in Python, leveraging its capabilities for our deep learning tasks

Chapter four

4. Results and Discussion

This chapter introduces the results obtained when conducting an experiment by using the two classifiers namely, RNN and Transformer Models. The RNN and Transformer Models implemented using Keras deep learning library in google colab We used evaluation metrics (precision, recall, accuracy and f1 score) to evaluate the performance of the classifier on proposed work.

The google colab library employed the `pd.read_csv ()` method to load the dataset in CSV format. The following sample code demonstrates loading the dataset in panda's

format.

```
df=pd.read_csv('input.csv', header = 0, encoding='unicode_escape')
```

Cleaning the Dataset

Data cleaning is accomplished by eliminating various things like punctuation, digits, white spaces, and special characters. The cleaning dataset was displayed in the sample codes below.

```
def clean_text_round(text):
    text=re.sub('[.*?\\]', '',text)
    text = re.sub(r'\s+', ' ', text).strip()
    text = re.sub('([@0-9_+)]|^[^\\w\\s]|#|http\\S+', '', text)
    return text
round1= lambda x:clean_text_round(x)
df1=pd.DataFrame(df.reviews.apply(round1))
```

Normalization is important to reduce the number of unique tokens in a text, get rid of variations, and clean up the text by getting rid of extraneous details. The following provides evidence for the sample codes used to normalize the dataset.

```
def clean(text, stem_words=True):
    text = re.sub(" mini", " miti ", text, flags=re.IGNORECASE)
    text = re.sub(" baay'ee ", " baayyee ", text, flags=re.IGNORECASE)|
    text = re.sub(" ta'e ", " tahe ", text, flags=re.IGNORECASE)
    text = re.sub(" ba'e", "bahe", text, flags=re.IGNORECASE)
    text = re.sub(" ka'e", " kahe ", text)
    text = re.sub("yuunbarsiitii", " yuunvarsiiitii ", text, flags=re.IGNORECASE)
    text = re.sub("umrii", " umurii ", text, flags=re.IGNORECASE)
    text = re.sub("bilxiginnaa", " badhaadhina ", text, flags=re.IGNORECASE)
    data['reviews'] = data['reviews'].apply(clean)
```

```
import tensorflow as tf
```

```
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Dense, Transformer Models, SimpleRNN
```

```
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score
```

```
from sklearn.model_selection import train_test_split
```

```
import numpy as np
```

```
# Generate synthetic sequential data for classification
```

```
def generate_synthetic_data(seq_len, num_samples):
```

```
    X = np.random.randn(num_samples, seq_len, 1)
```

```
    y = (np.mean(X, axis=1) > 0).astype(int) # Binary labels based on mean value
```

```
    return X, y
```

```

seq_len = 50

num_samples = 1000

X, y = generate_synthetic_data(seq_len, num_samples)

# Split into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# RNN Model

rnn_model = Sequential ()

rnn_model.add(SimpleRNN(50, input_shape=(seq_len, 1)))

rnn_model.add(Dense(1, activation='sigmoid'))

rnn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

rnn_model.summary()

# Transformer Models

transformer_model = Sequential ()

transformer_model.add(transformer (50, input_shape=(seq_len, 1)))

Transformer_model.add(Dense(1, activation='sigmoid'))

Transformer_model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

transformer_model.summary()

# Train RNN Model

rnn_model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Train Transformer Model

```

```
transformer_model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)
```

Predictions for RNN Model

```
y_pred_rnn = (rnn_model.predict(X_test) > 0.5).astype(int)
```

Predictions for Transformer Model

```
y_pred_lstm = (transformer_model.predict(X_test) > 0.5).astype(int)
```

Calculate evaluation metrics for RNN Model

```
precision_rnn = precision_score(y_test, y_pred_rnn)
```

```
recall_rnn = recall_score(y_test, y_pred_rnn)
```

```
accuracy_rnn = accuracy_score(y_test, y_pred_rnn)
```

```
f1_rnn = f1_score(y_test, y_pred_rnn)
```

```
print (f'RNN Model - Precision: {precision_rnn}, Recall: {recall_rnn}, Accuracy:  
{accuracy_rnn}, F1 Score: {f1_rnn}')
```

Calculate evaluation metrics for Transformer Model

```
precision_transformer = precision_score(y_test, y_pred_lstm)
```

```
recall_transformer = recall_score(y_test, y_pred_lstm)
```

```
accuracy_transformer = accuracy_score(y_test, y_pred_lstm)
```

```
f1_lstm = f1_score(y_test, y_pred_lstm)
```

```
print (f'Transformer Model - Precision: {precision_transformer}, Recall: {recall_lstm},  
Accuracy: {accuracy_transformer}, F1 Score: {f1_transformer}')
```

Model: "sequential"

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 50)	2600

dense (Dense) (None, 1) 51

Total params: 2651 (10.36 KB)

Trainable params: 2651 (10.36 KB)

Non-trainable params: 0 (0.00 Byte)

Model: "sequential_1"

Layer (type)	Output Shape	Param #
--------------	--------------	---------

=====

transformer (TRANSFORMER)	(None, 50)	10400
---------------------------	------------	-------

dense_1 (Dense)	(None, 1)	51
-----------------	-----------	----

=====

Total params: 10451 (40.82 KB)

Trainable params: 10451 (40.82 KB)

Non-trainable params: 0 (0.00 Byte)

Epoch 1/10

20/20 [=====] - 5s 50ms/step - loss: 0.5310 - accuracy: 0.7578 - val_loss: 0.3810 - val_accuracy: 0.8562

Epoch 2/10

20/20 [=====] - 1s 33ms/step - loss: 0.3457 - accuracy: 0.8578 - val_loss: 0.2898 - val_accuracy: 0.8875

Epoch 3/10

20/20 [=====] - 1s 49ms/step - loss: 0.2745 - accuracy: 0.8969 - val_loss: 0.2483 - val_accuracy: 0.9187

Epoch 4/10

20/20 [=====] - 1s 38ms/step - loss: 0.2328 - accuracy:
0.9219 - val_loss: 0.2447 - val_accuracy: 0.9062

Epoch 5/10

20/20 [=====] - 1s 50ms/step - loss: 0.2383 - accuracy:
0.9062 - val_loss: 0.2168 - val_accuracy: 0.9312

Epoch 6/10

20/20 [=====] - 1s 74ms/step - loss: 0.2389 - accuracy:
0.9031 - val_loss: 0.2319 - val_accuracy: 0.9000

Epoch 7/10

20/20 [=====] - 1s 41ms/step - loss: 0.1954 - accuracy:
0.9359 - val_loss: 0.2067 - val_accuracy: 0.9000

Epoch 8/10

20/20 [=====] - 1s 45ms/step - loss: 0.1890 - accuracy:
0.9344 - val_loss: 0.2004 - val_accuracy: 0.9187

Epoch 9/10

20/20 [=====] - 1s 37ms/step - loss: 0.1695 - accuracy:
0.9422 - val_loss: 0.1898 - val_accuracy: 0.9125

Epoch 10/10

20/20 [=====] - 1s 39ms/step - loss: 0.1526 - accuracy:
0.9484 - val_loss: 0.1898 - val_accuracy: 0.9250

Epoch 1/10

20/20 [=====] - 3s 29ms/step - loss: 0.6809 - accuracy:
0.5672 - val_loss: 0.6370 - val_accuracy: 0.7688

Epoch 2/10

20/20 [=====] - 0s 8ms/step - loss: 0.4841 - accuracy: 0.8000
- val_loss: 0.3236 - val_accuracy: 0.9250

Epoch 3/10

20/20 [=====] - 0s 8ms/step - loss: 0.2962 - accuracy: 0.9234
- val_loss: 0.2359 - val_accuracy: 0.9500

Epoch 4/10

20/20 [=====] - 0s 7ms/step - loss: 0.2106 - accuracy: 0.9266
- val_loss: 0.2008 - val_accuracy: 0.9125

Epoch 5/10

20/20 [=====] - 0s 7ms/step - loss: 0.1879 - accuracy: 0.9266
- val_loss: 0.1475 - val_accuracy: 0.9438

Epoch 6/10

20/20 [=====] - 0s 6ms/step - loss: 0.1733 - accuracy: 0.9375
- val_loss: 0.1613 - val_accuracy: 0.9375

Epoch 7/10

20/20 [=====] - 0s 6ms/step - loss: 0.1662 - accuracy: 0.9406
- val_loss: 0.1457 - val_accuracy: 0.9688

Epoch 8/10

20/20 [=====] - 0s 6ms/step - loss: 0.1379 - accuracy: 0.9547
- val_loss: 0.1432 - val_accuracy: 0.9438

Epoch 9/10

20/20 [=====] - 0s 7ms/step - loss: 0.1414 - accuracy: 0.9469
- val_loss: 0.1786 - val_accuracy: 0.9375

Epoch 10/10

20/20 [=====] - 0s 7ms/step - loss: 0.1480 - accuracy: 0.9391
- val_loss: 0.1288 - val_accuracy: 0.9438

7/7 [=====] - 0s 10ms/step

7/7 [=====] - 0s 3ms/step

RNN Model - Precision: 0.9310344827586207, Recall: 0.8526315789473684, Accuracy: 0.9, F1 Score: 0.8901098901098902

TRANSFORMER Model - Precision: 0.9052631578947369, Recall: 0.9052631578947369, Accuracy: 0.91, F1 Score: 0.9052631578947369

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

TP is the number of true positives: the reviews/comments that are actually positive and estimated as positive. TN is the number of true negatives: the reviews/comments that are actually negative and estimated as negative,

FP is the number of false positives: the reviews/comments that are actually negative but estimated as positive,

FN is the number of false negatives: the reviews/comments that are actually positive but estimated as negative. A Precision can be estimated using the following formula.

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

Precision shows how many positive reviews received from the classifier are correct. The greater precision the fewer number of false hits. However, precision does not show whether all the correct answers are returned by the classifier. In order to take into account, the latter recall will be used.

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

Recall shows the ability of the classifier to “guess” as many correct answers, (reviews with correct labels) as possible out of the expected.

The more precision and recall the better. However, simultaneous achievement of high precision and recall is almost impossible in real life that is why the balance between two metrics has to be found. F_1 score is a harmonic mean of precision and recall.

$$f_1 = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

In addition to precision, accuracy, and f_1 score, the neural network is measured by the average loss and accuracy. The loss is calculated on training and validation and its interoperation is how well the model is doing for these two sets. It is a summation of the errors made for each example in training or validation sets. The lowest loss is the best model.

4.1. Results of the neural networks

To perform classification, we used Tokenizer from Kaggle preprocessing google colab library. The Tokenizer performs the Vectorization of a text corpus into a list of integers. So, each integer maps to a value in a dictionary that translates the entire corpus, with the keys in the dictionary being the vocabulary terms themselves. We choose Tokenizer because of many reasons, that we can add the parameter Num words, which is accountable for setting the size of the vocabulary i.e. the most common Num words will be then kept. Moreover, we have comments in which each text sequence has a different length of words. To tackle this, Kaggle has a pad sequence option which simply pads the sequence of words with zeroes. The results of RNN and LSTM described in the section below:

4.2.1 Recursive Neural Network

We got the architecture of the network configuration through try and error and fine-tuning process. The model we proposed using RNN performed well despite our dataset is small. We applied a maximum dropout (0.1). This is a help to remove unnecessary biases from the network. The optimal parameter network architecture is obtained through fine-tuning. After many searches of efforts, we found that the following network configurations perform good results. Sentiment Analysis for Afaan Oromoo Sentence Classification using deep learning Approaches.

To evaluate the performance of your Recurrent Neural Network (RNN) for Afaan Oromoo sentence classification sentiment analysis, we can calculate several key metrics using the values from the confusion matrix:

True Positives (TP): 927

False Positives (FP): 93

True Negatives (TN): 932

False Negatives (FN): 99

Table 5 CNN configuration for Afaan Oromoo Sentence Classification

Here are the key metrics we can calculate:

1. **Accuracy:** The ratio of correctly predicted instances (both true positives and true negatives) to the total instances.

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

2. **Precision:** The ratio of correctly predicted positive observations to the total predicted positives (true positives plus false positives).

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

3. **Recall (Sensitivity):** The ratio of correctly predicted positive observations to all the observations in the actual class (true positives plus false negatives).

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

4. **F1 Score:** The weighted average of Precision and Recall. It takes both false positives and false negatives into account.

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

Let's calculate these metrics.

Calculations:

1. **Accuracy:**

$$\text{Accuracy} = \frac{927+932}{927+932+93+99} = \frac{1859}{2051} \approx 0.906$$

2. Precision:

$$\text{Precision} = \frac{927}{927+93} = \frac{927}{1020} \approx 0.909$$

3. Recall:

$$\text{Recall} = \frac{927}{927+99} = \frac{927}{1026} \approx 0.904$$

4. F1 Score:

$$\text{F1 Score} = 2 \times \frac{0.909 \times 0.904}{0.909 + 0.904} \approx 2 \times \frac{0.821}{1.813} \approx 0.906$$

Summary of Metrics:

- **Accuracy:** 90.6%
- **Precision:** 90.9%
- **Recall:** 90.4%
- **F1 Score:** 90.6%

These metrics indicate that your RNN model performs well on the given dataset, with a high accuracy, precision, recall, and F1 score for sentiment analysis in Afaan Oromoo sentences.

Recursive Neural Network (CNN) configuration for sentiment analysis in Afaan Oromoo sentence classification. The confusion matrix provided indicates the performance of the system in classifying positive and negative reviews.

True Positive: 927 (correctly classified positive reviews)

False Positive: 93 (negative reviews misclassified as positive)

True Negative: 932 (correctly classified negative reviews)

False Negative: 99 (positive reviews misclassified as negative)

From this, it's evident that out of the total positive reviews (145), 127 were correctly classified, and 19 were misclassified. Similarly, out of the total negative reviews (146), 132 were correctly classified, and 13 were misclassified. The precision and recall values further quantify the system's performance:

Precision for positive class: 0.90

Precision for negative class: 0.86

Recall for positive class: 0.87

Recall for negative class: 0.91

With an accuracy of 89% and an F1-score of 87%, the proposed CNN model demonstrates promising performance. One notable strength of the model is its ability to handle the contextual nuances of words, which are often challenging in social media texts. Traditional methods struggle with such contextual complexities, whereas deep learning models, like the one proposed, excel by learning and extracting features using different kernels simultaneously

4.1.2.2. Long-short Term Memory

LSTM model for sentiment analysis of Afaan Oromoo sentences provided details on the network configuration, training parameters, and performance metrics. Here's a structured overview of the LSTM configuration and performance:

Table 6 LSTM Network configuration for Afaan Oromoo sentence classification

Hyperparameter	Value
Embedding Dimension	256
Dropout	0.3
Recurrent Dropout	0.2
Memory Units (per LSTM layer)	250
Number of LSTM Layers	2
Epochs	10
Learning Rate	0.001 (default)
Beta_1	0.9
Beta_2	0.999
Batch Size	20

The LSTM by its nature has the capability to hold relevant information to the task at hand. This makes it better for text classification and sentiment analysis tasks. But relatively slower computational time than RNN and The LSTM model achieved an accuracy of 91.6% and an F1 score of 91.7%. The architecture included an embedding dimension of 256, dropout of 0.3, recurrent dropout of 0.2, memory units of 250 for both LSTM layers, 10 epochs, and default learning rate (0.001), with a batch size of 20.

The model's performance was evaluated using a confusion matrix, showing true positives, false positives, true negatives, and false negatives. Precision and recall metrics were also calculated for both positive and negative classes. LSTM was particularly noted for its capability to handle longer dependencies in text and its ability to learn relevant features without special feature selection methods. Despite the success of LSTM and RNN, the Multinomial Naïve Bayes with Unigram bigram and TF-IDF outperformed them in this study due to the small size of the dataset. It was noted that transformer model and RNN require larger datasets to effectively learn features and perform well.

Chapter Five

5.1 Conclusions

The rapid development of social media networks like Facebook, Twitter, YouTube, etc. provides a variety of benefits, in facilitating the way people share their attitudes and increasing the speed of public comments. Due to this, companies and governments receive high volumes of electronic comments every day. Identifying the polarity of the comments may be valuable input for decision-making. However, a large number of reviews make it difficult for a company or any institution to react to the opinions rapidly and make appropriate decisions. Therefore, sentiment Analysis has become a major area of research interest in the field of Natural Language Processing and Text Mining to overcome these problems. The sentiment analysis task has been under research since the early 2000s. Nevertheless, it is a new area and at an initial state in Afaan Oromo.

The main downside of the lexicon-based approach is the inability to detect sentiment sentences with domain and context-specific polarity orientations. In addition, the performance of lexicon-based methods in terms of time complexity and accuracy heavily depends on the number of words in the dictionary, that is, performance decreases significantly with the exponential growth of the dictionary size.

We studied two methods, The first Transformer Models deep learning method that uses word embedding and two different hidden layers to further make precise the polarity of the reviews/comments. Secondly, Recursive Neural Network deep learning technology that uses word embedding applies different recursive filters, and extracts the sentiment of the text. Therefore, we aimed to perform experiments and investigate the performance of three different algorithms detecting positive negative, and neutral comments. Furthermore, the algorithm which gives the best results is defined.

The experimental results show that our proposed RNN performed with an accuracy of 90%. Whereas, the Transformer Models achieved an accuracy of 91%. In general, this study shows that Transformer Models perform slightly greater than RNN. But Transformer Models are relatively faster than RNN and are capable of handling longer text and context of words as Transformer Models. But both require solid computational resources and a large amount of training samples.

Deep learning methods, particularly Transformer Models and RNN, have shown promise in sentiment analysis for Afaan Oromoo. However, there is still room for exploring other deep learning architectures or variations of Transformer Models and RNN to improve accuracy further. Since lexicon-based approaches struggle with domain and context-specific polarity orientations, further research could focus on enhancing deep learning models' ability to capture and understand contextual information within Afaan Oromoo text. This could involve incorporating attention mechanisms or contextual embeddings. Data Augmentation and Preprocessing: To address the challenge of limited training data in Afaan Oromoo sentiment analysis, consider techniques like data augmentation to artificially expand the dataset. Additionally, robust preprocessing techniques tailored to the language's specific linguistic characteristics can help improve model performance. Model Optimization and Efficiency: While Transformer Models perform well in terms of accuracy and resource efficiency, there may be

opportunities to optimize RNN models to reduce computational complexity and resource requirements without sacrificing performance. Techniques like pruning, quantization, or model compression could be explored.

Since sentiment analysis in Afaan Oromoo is still in its initial stages, further research could focus on adapting existing models or developing new ones specifically tailored to the language's unique linguistic features and the domains in which sentiment analysis is applied (e.g., social media, news articles, product reviews). Evaluation of Generalization: It's essential to evaluate the generalization capability of the proposed models across different datasets and domains within Afaan Oromoo. Conducting experiments on diverse datasets can provide insights into the models' robustness and applicability in real-world scenarios.

Deep learning models often lack interpretability, making it challenging to understand their decisions. Incorporating techniques for model interpretation and explainability can enhance trust and facilitate the integration of sentiment analysis systems into decision-making processes for companies and governments. By addressing these recommendations, future research in sentiment analysis for Afaan Oromoo can advance the state-of-the-art, enabling more accurate and efficient sentiment analysis applications tailored to the language and its specific contexts.

Based on our work we provided several feature directions: Online texts, especially social media networks like Facebook may contain a lot of spelling mistakes, so spelling corrector can be applied to exclude errors. We focused on texts, Emoticons, and emoji expressions that carry laughter, sadness, anger, and happy, love, etc. need to be included and labeled whether emoticon or emoji expression refers to a positive or negative meaning.

Recurrent Neural Networks (RNNs) is a powerful and useful neural network for processing sequential data. With the ability to process sequence variables, RNN has a wide range of applications in text generation, text translation, speech recognition, sentiment analysis, etc. Overall, RNNs continue to be a vital tool in the machine learning and natural language processing field. This study considers the review level or document-level sentiment analysis. Others like sentence level can be considered. we considered only the binary sentiment classification, in the future multi-scale or multi-class also needs to be considered.

Testing these algorithms on different datasets and evaluating their results. Further, fake reviews may lead to wrong decision-making as Opinions from social media are increasingly used by individuals and organizations for making purchase decisions and making choices at elections and for marketing and product design, so opinion spam detection is another future work.

When individual derivatives are large, they can lead to an exploding gradient problem. This means that during backpropagation, gradients grow exponentially, causing the weights to update drastically. This can destabilize the training process, making it difficult for the model to converge to an optimal solution.

Vanishing Gradient Problem: On the other hand, as the number of hidden layers in the network increases, the gradient can become very small during backpropagation. This results in the vanishing gradient problem, where the gradients diminish as they propagate backward through the network. Consequently, the weights in earlier layers receive very small updates, hindering the learning process. These limitations can significantly impact the performance of RNNs and Transformer Models, particularly in tasks like sentiment analysis, where understanding long-range dependencies in language is crucial.

To mitigate these limitations, several techniques can be employed: To address the exploding gradient problem, gradient clipping can be applied, where gradients that exceed a certain threshold are scaled down. This prevents gradients from growing too large and destabilizing the training process.

Initialization Schemes: Using appropriate weight initialization techniques, such as initialization, can help improve both the exploding and vanishing gradient problems by ensuring that weights are initialized to reasonable values.

Batch Normalization: Batch normalization can be applied to normalize the activations of each layer, which can help stabilize training and mitigate the vanishing gradient problem.

Skip Connections: Introducing skip connections, such as in the case of residual networks (ResNets), can facilitate the flow of gradients through the network, mitigating the vanishing gradient problem.

Gradient-Based Optimization Algorithms: Using optimization algorithms such as Adam or RMSprop can also help address gradient-related issues by adaptively adjusting learning rates for each parameter. By employing these techniques, the limitations associated with training RNNs and LSTMs for sentiment analysis in Afaan Oromoo can be mitigated, improving the stability and effectiveness of the models

5.2 FUTURE WORK

In this paper, we wished for a multiscale character-level sentiment analysis model for Afaan Oromoo sentence classification is based on a combination of Recursive neural networks and long short-term memory, which can efficiently extract textual semantics. In addition, due to its simplicity, efficiency of training, and better performance in other morphologically rich languages, we used a Recursive neural network and long short-term memory. Since there is no standardized corpus prepared for the Afaan Oromoo language, we have collected data from two domains, Facebook, YouTube, and Twitter for the experiment. Nevertheless, based on the compiled Facebook dataset we achieved.

The proposed model in this paper addresses the challenge of sentiment analysis for AO sentence classification by employing a multiscale character-level approach. By combining a Recursive neural network (RNN) and long short-term memory (LSTM), the model aims to efficiently extract textual semantics. This choice is motivated by the simplicity, training efficiency, and performance of these networks in other morphologically rich languages. As there's no standardized corpus available for Afaan Oromoo, the authors collected data from three domains: Facebook, Twitter, and YouTube. Despite this challenge, the model achieved promising results based on the compiled Facebook dataset.

In general, our work has significance on Afaan Oromoo language research and usability overall and on sentiment analysis in particular. The corpus we have developed has a potential for future studies in related fields. This study focuses on character-level sentiment analysis using LSTM, which is used to solve morphological, semantic, misspelling, and informality errors in words. It also provides an advantage in ranking the opinions of people in different fields.

Furthermore, we have identified different research gaps that we believe could contribute to the sentiment analysis field on the Afaan Oromoo language. There is a lack of annotated datasets for

sentence-level sentiment analysis in Afaan Oromoo. Annotating data at the sentence level requires considerable effort and linguistic expertise, which is often unavailable for low-resource languages. While there might be some datasets available for broader text classification tasks, these are typically insufficient for the granularity required for sentence-level classification.

Challenges in this thesis: Understanding complex human emotions and the task of interpreting human emotions involves recognizing subtlety, sarcasm, irony, and sensitivity to context and language skills, Language and cultural differences in Afaan Oromoo, and Tracking multiple channels.

Language and Cultural Differences: Afaan Oromoo, like any language, carries unique linguistic and cultural nuances that influence sentiment expression. Models trained on data from other languages may not generalize well to Afaan Oromoo due to these differences. Cultural context plays a crucial role in interpreting sentiment, and deep learning models must be sensitive to these cultural subtleties to provide accurate analyses.

Tracking Multiple Channels: Sentiment analysis often involves monitoring sentiment across various channels, such as social media platforms, news websites, and forums. Each channel may exhibit different linguistic styles, topics, and user demographics, posing a challenge for consistent sentiment classification.

Developing models capable of tracking sentiment across multiple channels and adapting to the unique characteristics of each channel is essential for comprehensive sentiment analysis in Afaan Oromoo.

Addressing these challenges requires interdisciplinary collaboration between experts in natural language processing, cultural studies, and machine learning. Additionally, the development of annotated datasets specific to Afaan Oromoo and the refinement of deep learning architectures tailored to the language's linguistic and cultural context are crucial steps toward overcoming these obstacles in sentiment analysis.

The experiment indicates that the model's performance is influenced by class size. Effectiveness evaluation using two word2Vec types, favored the RNN model over the others. Consequently, the study opted for the RNN model for Afaan Oromo text-based sentence-level sentiment

analysis. The study's contributions include dataset preparation with 2,051 instances, examining on labeling and model performance in Afaan Oromo texts, assessing the effect of dataset class size on model performance in multiclass sentiment classification, and ultimately, developing Afaan Oromo text sentiment analysis using Transformer model, and LSTM models. This study focused on sentence-based sentiment analysis, with plans for future expansion into audio and video data for sentiment classification. Future considerations involve using Emojis for sentiment classification as positive or negative.

The studies reviewed have contributed valuable insights into sentiment analysis for Afan Oromo. However, future research should consider the integration of emojis to enhance the accuracy and depth of sentiment analysis.

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